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# Biodiversity impact assessment of the aquaculture industry in Norway - a company level application

Master's thesis in Industrial Economics and Technology Management
Supervisor: Maria Lavrutich
Co-supervisor: Verena Hagspiel
June 2022

Master's thesis

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# Abstract

This thesis investigates the biodiversity impact of aquaculture companies in Norway. By utilizing publicly available data from 2016 to 2021 on the biodiversity impact variables sea lice, escapes, diseases, bottom conditions and lice treatments from the 36 largest salmon farming companies in Norway, we find which companies that have the best and worst impact on biodiversity and the different impact variables during that period. We apply an unsupervised clustering approach to classify the companies based on their biodiversity impact performance before aggregating the number of times a company ends up in each cluster to rank and compare the companies against each other. We find that companies operating in the northern production areas in Norway perform better on our biodiversity impact variables than the companies operating in the southwestern production areas. These results can be explained mainly by sea lice numbers and disease outbreaks, where salmon farming companies in the north have a geographical advantage due to lower sea temperature and density of localities. When we split our data into two regions, one for production areas 1-6 in the south and one for production areas 7-13 in the north, we find that the larger and publicly traded salmon farming companies perform especially well. Through a regression analysis, we also find that other biodiversity measures become more influential when we split the data set between southwest and north as opposed to the nationwide comparison. Finally, we investigate and discuss the quality of the reported data we use when assessing companies' performance on biodiversity impact variables. Overall, our findings contribute to the growing literature on biodiversity impact assessments of companies by developing an assessment framework on company level tailored for the Norwegian aquaculture industry, and our results shed light on important biodiversity impact patterns from the aquaculture industry.

# Preface

As our final part of the way to achieving a Master of Science degree at NTNU, we have produced this master's thesis equivalent to 30 credits. Specializing in Financial Engineering at the Department of Industrial Economics and Technology Management, work on this thesis was conducted from January to June 2022.

The problem statement we are looking into in this master thesis was initially presented by DNB. There is currently a lack of structured and standardized methods on how to assess biodiversity impacts on a company level within the aquaculture domain, and DNB asked us to fill in on this. We are thus aiming to provide decision support from a biodiversity impact perspective, supporting financial institutions, companies, regulatory authorities and other stakeholders with an interest in biodiversity impact performance of salmon farming companies to make responsible investment decisions and ensure further sustainable growth of the industry. There is a growing attention towards biodiversity impact assessments on company and portfolio level, and it is an area only believed to further increase relevance and importance in the future. We build upon the qualitative approach used in our project thesis, further extending it through a more data driven approach including more companies and years in order to provide the best decision support, results and insights possible. Coding has been used extensively to extract and systematize data for the company level biodiversity impact performance comparison. This code will be made available to the reader upon request.

We want to thank our supervisors, Maria Lavrutich and Verena Hagspiel, for ideas, discussions and important viewpoints during the process. We are also thankful to our main point of contact in DNB, Audun Wickstrand-Iversen, as it has been very valuable to get input on our work from a portfolio managers point of view.

Trondheim, June 10th, 2022

Markus B. Jansen — Gaute Nepstad

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# 1 Introduction

The current extinction rate of species is tens to hundreds of times higher than the average over the past 10 million years, and it is accelerating (IPBES 20019). Biodiversity is our planet's "living tissue" and the ultimate source of all ecosystem services on which our civilization depends on (such as the supply of raw materials, pollination, air quality, water quality, and climate regulation). Biodiversity is also central to the long-term sustainability of economic activities. Most industries use and therefore depend directly and indirectly on natural resources and ecosystem services (CDC Biodiversité' 2017). Thus, the current erosion of biodiversity poses a considerable risk to the financial markets and economic development. An estimated investment of up to USD 967 billion is required each year to reverse the decline in biodiversity by 2030 (Deutz et al. 2020). As a result of this, and other environmental issues such as climate change, a wide variety of tools and methodologies have been developed to support the integration of ESG (Environmental, Social, and Governance) factors into the business and investment processes of financial institutions. These factors have mainly been used in risk assessment or management. However, the finance sector ESG integration has not yet demonstrated a significant focus on the impacts such institutions can have on the environment, people, and biodiversity (Hilton et al. 2021).

This lack of focus on impact is starting to change due to several emerging trends. From a regulatory perspective, the EU's Sustainable Finance Action Plan (SFAP) and its key components such as the EU Taxonomy, which aims to define what economic activities are environmental sustainable, and the Sustainable Finance Disclosure Regulation (SFDR), which aims to better classify the sustainability credentials of investment funds (EU 2020). Other vital efforts to improve sustainability and biodiversity disclosure are also underway.[1] All of these initiatives acknowledge the "double materiality," indicating that sustainability issues are firstly a risk or opportunity for the financial sector, and secondly, that financial flows influence the environment and biodiversity (PwC 2020). Much of the foundation of these trends come from the establishment of the Sustainable Development Goals (SDGs 2015) by the United Nations in 2015, in which SDG 14 (Life Below Water) and SDG 15 (Life on Land) are especially relevant for biodiversity. The SDGs added an explicit impact orientation to the investing domain. However, biodiversity has lagged behind other non-financial factors, such as climate change, that investors need to assess, analyze and integrate into their activities despite being closely linked (Credit Suisse 2021).

An industry that has a crucial role in helping to achieve several of the UN's SDGs by 2030 is the aquaculture industry (EIT 2021). Although not yet a part of the EU Taxonomy, it is likely to be included later (Ahlstrand 2021; Aquaculture Advisory Council 2021). In Norway, the salmon farming industry has grown from a niche market to a massive industrial adventure, as salmon production has ten doubled since 1992 and doubled since 2005. Half of the world's salmon supply in 2021, over 1,5 million tonnes of Atlantic salmon, was produced in Norway (The Directorate of Fisheries 2021; FAO 2021). As production has grown, the environmental and biodiversity impact of the industry has also increased. The salmon production industry affects the wild salmon populations, the coastal fisheries, and the sea floor due to environmental pollution (Olaussen 2018). One of the most prominent problems is maintaining the wild salmon stock, which spawns in the rivers of Norway, as Norway holds about 25% of the world's healthy populations (Hindar et al. 2011). Furthermore, studies show that the two most severe challenges concerning the wild salmon are escapes from fish farms and their high sea lice densities (Forseth et al. 2017; Thorsdad et al. 2017). As a result, the Atlantic wild salmon has been added to the "red list", a database of threatened, endangered, and extinct species in Norway, with the status "near threatened" (Norwell 2021).

In this thesis, we focus on measuring and assessing the Norwegian salmon farming industry's biodiversity impact on a company level. A challenge associated with measuring and assessing biodiversity at the company and portfolio level is that the high number of variables involved makes it difficult to reduce the measurement to a single number. In addition, important data is often missing or can be of poor quality. Biodiversity-related impacts are location-dependent, contributing to the difficulty of measuring impact, even within a single company (Hilton et al.

[1] In particular, the establishment of the Taskforce on Nature-related Financial Disclosures (TNFD 2022) and the development of sustainability disclosure standards by the International Sustainability Standards Board (ISSB 2022).

2021). However, a few tools have been developed by scientists and organizations. In the current literature, several studies have investigated how to develop and define biodiversity impact indicators to be used by company managers, investors and financial institutions (Bell et al. 2008; Biodiversity Indicators Partnership 2011; Pereira et al. 2013; Maxwell et al. 2014; Natural Capital Coalition 2016; Addison et al. 2018). Another stream of literature has focused on identifying, describing, and categorizing the different tools that have been developed to assess the biodiversity impacts of companies and portfolios (Neveux et al. 2018; Hilton et al. 2021; EU Business and Biodiversity Platform 2021). Hilton et al. (2021) classify the impact measurement tools into SDG-related and biodiversity-related tools, in which the tool we develop in this thesis can be placed in the latter category. However, our biodiversity impact assessment methodology stands out from existing biodiversity impact assessment tools and contributes to the literature in several ways. First, we use specific biodiversity impact variables and indicators for the Norwegian aquaculture industry, which is not, to our best knowledge, used by the existing biodiversity footprinting tools. Secondly, our methodology assesses the biodiversity impact of salmon farming companies over a substantial amount of time. At the same time, many existing tools only provide a snapshot of the current impact of the analyzed company. Lastly, we use official databases with data reported and monitored by regulatory authorities in Norway instead of relying on company disclosures and third-party data collecting companies. The data reporting for these sources is not standardized, and quality is not checked the same way.

The environmental and biodiversity impacts from the Norwegian salmon farming industry has gained substantial attention in the literature, which has identified the following main impacts: escapes of farmed salmon (Grimnes et al. 1996; Fleming et al. 2000; McGinnity et al. 2004; Hindar et al. 2006; Krkošek et al. 2006; Skilbrei et al. 2014; Karlsson et al. 2016; Glover et al. 2017; Overton et al. 2019), the effect of high densities of sea lice (Holst et al. 2003; Heuch et al. 2005; Fjørtoft et al. 2017), spread of infectious diseases (Taranger et al. 2015; Madhun et al. 2022; Sommerset et al. 2021), medicinal usage in relation to delousing treatments (Olaussen 2018; Overton et al. 2019; Grefsrud et al. 2021), and environmental impacts on the seabed (Mente et al. 2006; Taranger et al. 2015; Grefsrud et al. 2021). However, most studies do an impact assessment at the industry level. They do not examine how to develop effective and relevant biodiversity impact indicators specific to the Norwegian salmon farming industry companies. This thesis aims to fill the current gap in the literature related to biodiversity impact assessment of the Norwegian salmon farming industry on a company level by developing an assessment tool utilizing an unsupervised machine learning methodology. We utilize publicly available data[2] in order to develop indicators that measure and compare biodiversity impact performance on a company level based on the variables lice counts, escapes, diseases, lice treatments and bottom condition surveys.

Then we utilize an unsupervised clustering methodology to rank companies based on their biodiversity impact performance. First, we employ this methodology nationwide, comparing all the companies in our sample on all the five biodiversity impact indicators mentioned above. The results from our model show a strong correlation between a company's biodiversity impact performance and geographical location, indicating that companies operating in the southern- and western part of Norway perform worse on biodiversity impact than companies operating in the northern part of Norway. A higher locality-density could explain this in fjords of the southern- and western areas and warmer average sea temperatures, which result in more spread of sea lice and diseases (Godwin et al. 2020; Oliveira et al. 2021).

Second, we use our clustering methodology separately on each of our five biodiversity impact indicators to investigate which of the indicators affect the overall clustering score the most. To further examine the relative importance of the biodiversity impact variables to the overall biodiversity impact score for a company, we employ an ordinary least square regression analysis. The results of our regression model show that the biodiversity variables impacting the overall biodiversity score the most are lice counts, diseases, and bottom survey scores. The results imply that an improvement in a company's cluster placement on sea lice numbers, bottom survey scores, and the number of diseases is most influential towards its overall biodiversity impact performance score. The results also show that the geographic location of a company's operations affects the score, as on average, companies operating in the southwestern areas of Norway get worse scores. Finally, the

[2]Using data made available by BarentsWatch, The Directorate of Fisheries, and The Norwegian Food Safety Authority.

regression analysis shows that company size affects the overall biodiversity impact score, indicating that more prominent companies perform slightly poorer than smaller salmon farming companies when compared nationwide.

Third, since the first nationwide clustering model showed a strong correlation between a company's overall biodiversity score and geographic location in Norway, we split the data set between companies operating in southwestern and northern areas of Norway. This way, we make more fair comparisons between companies facing similar geographical challenges regarding temperature and locality density. Only four out of the 36 companies in our data set operate in both defined areas, and we split these companies' operations between the two areas. Our results show that all six publicly traded companies end up among the top performers in Norway's southern- and western areas on biodiversity impact performance. For companies operating in the northern areas of Norway, the listed ones get placed among the top half out of the 21 companies operating in the north. We also find the same results through regression analysis on the clustering score results from the split data set, that larger salmon farming companies perform slightly better than smaller companies in both regions, which was not the case from the nationwide comparison. Potential explanations of the observed differences between private and publicly listed companies could be that the large listed salmon farmers focus more on sustainability and transparency to attract investors and better routines due to a more extensive base of experience and resources.

To finalize our data analysis, we perform a robustness check of our results by employing dynamic time warping to cluster time series. Robustness analysis is needed for our results as our clustering methodology is a novel assessment approach that considers both time series and non-time series data by aggregating them annually. Thus, we examine our approach's robustness by applying our methodology and a classical time series clustering to the suitable variables and comparing the results. Time-series clustering approaches has earlier been used in the literature to cluster companies based on financial time series data (Focardi 2002; Todorovski et al. 2002; Basalto et al. 2007; Piccardi et al. 2011). We use our time series clustering methodology on the biodiversity impact variables showing the strongest time-series properties in the data; lice counts, diseases, and treatments. The dynamic time warping clustering method results show that our biodiversity impact clustering methodology is robust as a biodiversity assessment tool. It correctly places the top nine and worst nine companies in terms of impact performance with an accuracy of 94%.

Lastly, using interviews with several representatives from regulatory institutions monitoring the industry as a starting point, we provide an extensive review and discussion on the data quality of our selected biodiversity impact variables. Key insights from these interviews are that the data quality on escapes is poor, mainly due to uncertain numbers of salmon in the pens before the incidents happen. For the other variables, the data quality ranges from medium (lice counts) via medium/high (bottom condition surveys) to high (lice treatments and diseases). The biodiversity impact variable showing the most negligible influence on the overall biodiversity impact scores is the escape variable. Hence, the poor quality of that variable has a minor effect on the robustness of our results.

Overall, our method provides insights into the relative biodiversity impact performance of companies in the Norwegian aquaculture industry. This way, companies within the industry can be measured and compared on their biodiversity footprint. Financial institutions can utilize our results to align their investment strategies with biodiversity impact targets. The insights are also helpful for regulatory authorities responsible for the industry's sustainable growth. Our methodology can help determine which companies should be granted permission for production growth based on their biodiversity impact. Our biodiversity impact assessment framework of aquaculture companies provides a more holistic evaluation of whether a company should be permitted to increase their production than today's system, which is solely based on the mortality of wild salmon due to sea lice (Fagerbakke 2020). The assessment results could also be helpful for the companies themselves. They could use them to benchmark their biodiversity impact performance against their competitors. In addition, best-performing companies could use the assessment results to attract financing and lower their cost of capital as bank loans, bonds, and equity are increasingly pointed toward supporting sustainable and biodiversity-friendly companies and projects (Baker et al. 2018; Loan Market Association 2018).

Our thesis contributes to the financial literature in several ways. First, it contributes to the growing literature on biodiversity impact assessment of companies and portfolios (Bell et al. 2008; Biodiversity Indicators Partnership 2011; Pereira et al. 2013; Maxwell et al. 2014; Natural Capital Coalition 2016; Addison et al. 2018). Compared to the existing literature, we develop specific impact indicators and an assessment framework tailored for the Norwegian aquaculture industry and therefore contribute to the literature on industry-specific biodiversity impact assessments (Beliaeff et al. 2011; Slay 2019), extended to a company level assessment methodology. Moreover, we expand the literature on biodiversity impact assessments by using a novel approach to usage of unsupervised machine learning methods, clustering, and ranking companies based on their biodiversity impact performance. Hence, we also contribute on the existing literature on clustering of companies by using specific biodiversity impact indicators as variables (Jamali et al. 2009; Afonso et al. 2012; Ortas et al. 2015; Jitmaneeroj 2016; Iamandi et al. 2019; Perchinunno et al. 2020). Second, through a comprehensive review of existing literature on environmental and biodiversity impacts from the Norwegian aquaculture industry, we have developed effective and relevant biodiversity impact indicators for the industry on a company level. Finally, we contribute to the literature on biodiversity impacts from the Norwegian salmon farming industry with an extensive review and discussion on the data quality of our chosen biodiversity impact indicators. Through several interviews with representatives of the regulatory authorities monitoring the industry and a thorough literature review, we provide insight into the reliability of the data behind our biodiversity variables. Consequently, our novel contribution to financial literature is to shed light on important biodiversity impact patterns for Norwegian salmon farming that can provide key insights to financial institutions, companies, and regulatory authorities to ensure the industry's sustainable growth further.

The structure of this thesis is the following. Section 2 gives an overview of the relevant literature on biodiversity impact assessments of companies and portfolios, environmental and biodiversity issues with the Norwegian salmon farming industry, and clustering of firms. Section 3 contains an overview of the selected biodiversity impact variables, data cleaning process, and the final data set. Section 4 explains the methods used to provide our results and findings. Section 5 and Section 6 present and discuss the results. Finally, Section 7 concludes the thesis and presents suggestions for further research.

## 2 Literature Review

Our thesis contributes to several strands of literature. First, we add to the growing literature on biodiversity impact assessments in finance and their importance. Impact investments and biodiversity impact assessments have received increased attention in the ESG, sustainable finance, and responsible investments studies. As defined by the Impact Management Project, which provides a forum for building global consensus on how to measure, manage, and report impacts on sustainability, impact is "a change in an outcome caused by an organization. An impact can be positive or negative, intended or unintended." (IMP 2021). Some studies have investigated the connection between biodiversity and finance, and why it is important for the finance industry to invest in biodiversity (Rubino 2002; Parker et al. 2012; Sumaila et al. 2017; Smith et al. 2018). Sumaila et al. (2017) find that the benefits of investing to meet the Aichi Targets[3] set by the Convention on Biological Diversity (CBD) outweighs the costs in terms of monetary and non-monetary benefits of biodiversity conservation. Smith et al. (2018) map the SDGs to the five Aichi Targets into "corporate biodiversity goals". The authors present fourteen different case studies to illustrate necessary actions to reach the goals and translate them across different business sectors with varying scales, locations, and forms of biodiversity while highlighting the financial, societal, and environmental benefits.

Several studies have also focused on how to develop and define biodiversity impact indicators to be used by company managers, investors and financial institutions (Bell et al. 2008; Biodiversity Indicators Partnership 2011; Pereira et al. 2013; Maxwell et al. 2014; Natural Capital Coalition 2016; Addison et al. 2018). They have developed scientific frameworks explaining how to approach the task of finding biodiversity impact indicators and measuring a company's total biodiversity impact. Biodiversity Indicators Partnership (2011) defines an indicator as "a measure or metric based on verifiable data that conveys information about more than itself", and examines the multiple uses of biodiversity indicators, such as for reporting and investment decisions. Further, the authors present their Biodiversity Indicator Development Framework, which contains key steps in successful indicator development. Pereira et al. (2013) contribute to this stream of literature by defining "Essential Biodiversity Variables" to supply the measures set by CBD to reach the Aichi Targets. Addison et al. (2018) introduce a spectrum that outlines four prominent scopes for business application biodiversity indicators. The scopes range from biodiversity management and performance at the individual site and landscape-level to rating a whole company. The authors identify and emphasize that there is a lack of indicators that measure corporate-level biodiversity impacts. They state that developing corporate-level biodiversity state indicators could help better assess corporate biodiversity performance. Bell et al. (2008) provide details on how to define sustainability indicators, including biodiversity indicators, scientifically. Another developed decision-making framework is The Natural Capital Protocol (Natural Capital Coalition 2016) by the IUCN's Natural Capital Coalition that enables organizations to identify, measure and value their direct and indirect impacts and dependencies on natural capital[4].

Other studies within this stream of literature focus more on identifying and describing different tools that have been developed to assess the biodiversity impacts from a portfolio perspective (Neveux et al. 2018; Hilton et al. 2021; EU Business and Biodiversity Platform 2021). The contributions here typically come from prominent organizations, and the mentioned tools are created primarily as initiatives. These tools apply mainly "footprint" approaches, which use various data sources, including corporate disclosures, estimated data, and third-party databases, to calculate the relevant impacts for the chosen ESG/SDG/biodiversity variables involved. Hilton et al. (2021) summarize the tools to measure biodiversity and SDG footprints of financial portfolios and categories them into holistic and issue-specific. Table 1 presents a summary of the primary listed tools. For holistic tools such as those focusing on ESG or SDG factors, these outputs tend to be wide-ranging, involving everything from greenhouse gas emissions to the number of employees. These metrics are aggregated by company to the portfolio level and are compared to a reference benchmark. Biodiversity footprinting tools (issue-specific) have a more narrow focus. However,

[3] 20 targets that address each of five strategic goals set by the Convention on Biological diversity to reduce biodiversity loss.

[4] The world's stocks of natural resources, including soil, air, water and all living things from which humans derive a wide range of services that make human life possible (CBD 2022)

they examine the issue more thoroughly, trying to scientifically capture a company's biodiversity impact, including its upstream and downstream effects. Usually, this includes some form of product life cycle or value chain analysis crosslinked to the physical locations involved in the company's activities and the various biodiversity pressures involved. To make it easier for non-specialists to understand the outputs, the results are translated into a single metric reflecting species availability, such as the metric Mean Species Abundance[5] (MSA in km2). Neveux et al. (2018) follows a similar strategy to summarize and describe 11 existing methodologies and tools to evaluate biodiversity performance. The authors are grouping them into three different categories; "Foundational biodiversity data & tools", "Guidelines for integrating biodiversity in decision support tools", and "biodiversity decision support tools". The authors emphasize that footprinting tools generally only capture a snapshot in time and thus can be challenging to use to support forward-looking risk or impact monitoring approaches. Hilton et al. (2021) state that key sources of uncertainty in the existing tools are update frequency of data and model granularity. For timing, some elements of the tools may utilize datasets where the most recent data available is several years in the past or updated only every several years. Regarding granularity, the authors emphasize that tools utilizing sector- or country-level averages as part of their calculations may pose difficulties related to reflecting meaningful changes that occur at a smaller scale. Following Hilton et al. (2021, Table 1) classification of tools, our developed assessment method places itself as follows: focus: biodiversity-specific, target: companies/portfolios, measurement type: relative and ease of use: relative impact. However, our biodiversity impact assessment methodology stands out from the existing biodiversity footprinting tools in several ways. First, we use specific biodiversity impact variables and indicators for the Norwegian aquaculture industry, which is not, to our best knowledge, used by the existing biodiversity footprinting tools. Secondly, our methodology assesses the biodiversity impact of salmon farming companies over a substantial amount of time. Many existing tools only provide a snapshot of the current impact from the assessed company. Lastly, we use official databases with data reported and monitored by regulatory authorities in Norway instead of relying on company disclosures and third-party databases. The data reporting is not standardized, and quality is not checked the same way.

| **Name** | **Provider** | **Assessment Focus** | **Assessment Target** | **Impact Measurement Type** | **Ease of use** |
|---|---|---|---|---|---|
| Corporate Biodiversity Footprint | Iceberg Data Lab | Biodiversity-specific | Companies / Portfolio | Absolute | Fully automated |
| Biodiversity Impact Analytics | CDC Biodiversité / Carbon4 Finance | Biodiversity-specific | Companies / Portfolio | Absolute | Fully automated |
| Biodiversity Footprints for Financial Institutions | ASN Bank / PRé / CREM | Biodiversity-specific | Bank Balance Sheet | Absolute | Partially automated |
| Net Environmental Contribution metric | Sycomore AM et al. | General E focus | Companies / Portfolio | Relative | Partially automated |
| Portfolio Impact Footprint | Impact Cubed | SDG | Investment Portfolio | Relative | Fully automated |
| Sustainable Investment Framework Navigator | KMPG / CISL | SDG | Investment Portfolio | Relative | Fully automated |
| Portfolio Impact Analysis Tool for Banks | UNEP FI Positive Impact Initiative | SDG | Bank Business Lines | Relative | Partially automated |

Table 1: Relevant existing impact measurement/footprinting tools for investors and other financial institutions. Source: WWF (2021)

A large body of research within biodiversity impact assessments also focuses on frameworks and indicators for a specific industry, project, or area (Beliaeff et al. 2011; Slay 2019). Slay (2019) demonstrates how biodiversity indicators and metrics can be found for agricultural products from Life Cycle Impact Assessment (LCIA) on an ecoregional scale and a local/farm scale. Beliaeff et al. (2011) examine the desirable characteristics of indicators that provide decision support for marine environmental management. The authors assess indicators according to two criteria: relevance and effectiveness. Relevance of indicators encompasses sensitivity and quantitative reference values, thereby allowing the selection of potential indicators. Effectiveness is the ability of the indicator to reach its predefined targets based on optimal data collection protocols. To the best of our knowledge, no studies have developed biodiversity impact indicators specific to the salmon aquaculture industry. The closest biodiversity impact assessment for the aquaculture sector we have identified

[5]MSA is an indicator of naturalness or biodiversity intactness. It is defined as the mean abundance of original species relative to their abundance in undisturbed ecosystems. An area with an MSA of 100% means biodiversity similar to a pristine state. An MSA of 0% means all original species are locally extinct. (GLOBIO 2021)

is research done by the FAIRR Initiative (2022) through their Protein Producer Index, which is an assessment of the largest animal protein producers on critical ESG issues. They include some of the same biodiversity impact variables we do but rely on company disclosures instead of using official data sources provided by regulatory authorities as our assessment methodology does. Hence, the data is less standardized, and the quality of the data depends on how transparent the company is. In addition, they only consider the largest listed salmon farming companies while we assess and compare a large set of listed and privately owned salmon farming companies. Therefore, we extend the current literature on biodiversity impact assessments of businesses in investment decisions by using inspiration from existing footprinting tools to develop biodiversity indicators specifically for the Norwegian aquaculture industry on a company level based on existing data sets.

Secondly, we contribute to the literature on environmental and biodiversity issues in the Norwegian aquaculture industry. To develop biodiversity impact indicators for Norwegian fish farming companies, we follow two criteria (Beliaeff et al. 2011): relevance and effectiveness. Olaussen (2018) addresses the environmental and biodiversity issues associated with Norwegian salmon farming and presents data on these problems. Adding to this, Grefsrud et al. (2021) summarize environmental issues from the industry in a risk report published annually by the Norwegian Institute of Marine Research. The main environmental and biodiversity impacts from the Norwegian aquaculture industry considered in these papers are the following; escapes of farmed salmon, the effect of sea lice, diseases, medicinal usage concerning delousing treatments, and environmental impacts on the seabed. The existing studies do not combine these biodiversity impact variables in one assessment, as we do in this thesis. Hence, we contribute to the existing literature on biodiversity impact from the aquaculture industry by combining five of the most influential variables in one biodiversity impact assessment of the salmon farming industry, providing a more holistic assessment methodology.

There exists a large body of literature studying biodiversity impacts due to escapes of farmed salmon. The main research areas in these studies are estimation of actual escape numbers (Skilbrei et al. 2014; Thorsdad et al. 2017), effects due to interaction and interbreeding with wild salmon (Fleming et al. 2000; McGinnity et al. 2003; McGinnity et al. 2004; Hindar et al. 2006; Karlsson et al. 2016; Fjørtoft et al. 2017; Forseth et al. 2017; Glover et al. 2017) and increase of sea lice pressure on wild salmon due to escaped farmed salmon (Grimnes et al. 1996; Bjørn et al. 2002; Gargan et al. 2002; Krkošek et al. 2006). Thorsdad et al. (2017) calculate that farmed salmon escapes constitute around half of the yearly in-run of wild Atlantic salmon to Norwegian rivers. Skilbrei et al. (2014) estimate that the actual numbers of escapees in Norway were 2-4 times higher than the numbers reported by fish farmers from 2005 to 2011. Key insights from these studies are that wild and farmed salmon interact through competition, predation, hybridization, colonization, and spreading diseases and parasites, which leads to increased mortality of the wild salmon (Forseth et al. 2017). In addition, interbreeding between escaped farmed and native salmon reduces the fitness and productivity of the wild salmon and dilutes the genetic material pools threatening the survival of the native salmon offspring (Glover et al. 2017). Inspired by these studies on the biodiversity impacts from escapes, we choose to include the escapement of farmed salmon as one of our indicators of biodiversity performance for Norwegian fish farmers.

Many studies also focus on the problem with sea lice, which are external parasites living on the salmon's skin. Heuch et al. (2005) emphasize the biodiversity impacts of sea lice by showing how the aquaculture industry contributes to the sea lice density in the Norwegian fjords, while other studies (Holst et al. 2003; Fjørtoft et al. 2017) document how smolt infected by sea lice has increased mortality. However, many studies emphasize that it is impossible to estimate how much the smolt survival is reduced due to sea lice-induced mortality on a national scale (Olaussen 2018). The effect of sea lice varies between fjords and from river to river. Thorsdad et al. (2017) estimated that the annual loss of wild salmon to Norwegian rivers is about 10% on a national level. Due to these reasons, Forseth et al. (2017) rank the high sea lice densities, together with escaped farmed salmon from aquaculture, as the two most significant and expanding threats to the wild salmon populations in Norway. Hence, in this thesis, we also include sea lice numbers as an indicator of biodiversity performance for Norwegian fish farming companies.

In order to cope with the increasing sea lice problems, a range of chemical and mechanical treatments have been tested. As a result, some studies have examined the effect on the environment and biodiversity due to these treatments as chemical treatments also affect other crustaceans species and fish (Grefsrud et al. 2021). The problem with chemical treatments is that the sea lice seem very adaptable. It can take years for evidence of resistance to appear following a new treatment with a new chemical. One solution has been to switch between different treatment methods, but the problem of resistance seems hard to overcome, and multi-resistance has emerged (Olaussen 2018). In recent years, freshwater treatment has also become part of the solution, and many in the industry fear that the sea lice will also develop more tolerance for freshwater. Overton et al. (2019) detect a rapid paradigm shift in the industry's approach to lice control from medicinal treatments to non-medicinal operations but note that these non-medicinal operations are associated with high mortality rates. The sea lice treatments also represent a substantial cost to the industry—some companies in the scale of up to 13% of yearly revenues (Abolofia et al. 2017). Hence, we include lice treatment as a biodiversity impact performance indicator for Norwegian fish farmers.

Among other factors necessary to consider from the perspective of biodiversity impacts are diseases and environmental bottom impacts. However, these topics have received less attention in the literature. Infectious diseases represent a problem for fish farming, despite the successful development and application of vaccines against a range of pathogens (Taranger et al. 2015; Madhun et al. 2022). Diseases that are required by law to notify the Norwegian Food Safety Authority are divided into list 1 (exotic), list 2 (non-exotic), and list 3 (national). Diseases on list 1 have never been identified in Norway, but diseases on lists 2 and 3 have been reported amongst Norwegian fish farms in recent years (Sommerset et al. 2021). Outbreaks of Infectious salmon anemia (ISA, list 2) and Pancreatic disease (PD, list 3) are the only disease outbreaks made publicly available by the Norwegian Food Safety Authority. A wide range of other diseases was discovered in 2021, which caused increased mortality amongst Norwegian farmed salmon but lack publicly available data (Sommerset et al. 2021). Therefore, we only consider ISA and PD outbreaks in our biodiversity impact assessment of the industry. Studies that have examined the environmental bottom impacts emphasize that increased awareness of high discharges of nutrients, excess feed, and feces to the marine environment has resulted in greater scrutiny of the aquaculture industry (Mente et al. 2006; Taranger et al. 2015; Grefsrud et al. 2021). The Directorate of Fisheries state that "the environmental impact of aquaculture must be kept at an acceptable level and be within the assimilate capacity of the area" (The Directorate of Fisheries 2009). Therefore, Norwegian fish farmers must perform mandatory bottom surveys called MOM-B at regular intervals. These surveys have to be done according to Norwegian Standard document "NS-9410" [6], where the output scores range from 1 to 4, where 1 is defined as "very good" and 4 is "very bad" in terms of environmental bottom condition impacts under the location. Based on existing evidence, we include diseases and bottom condition survey scores as biodiversity impact performance indicators in our thesis.

All literature we have examined has in common that they focus on the aquaculture industry in Norway as a whole and do not focus on how to separate the different companies in terms of environmental and biodiversity impact performance. Therefore, we extend the current literature on biodiversity impact assessment of the Norwegian fish farming industry by developing key biodiversity indicators and introducing a framework to measure and compare fish farming companies based on biodiversity performance.

Lastly, our thesis is related to the literature on the clustering of firms based on environmental performance characteristics. In order to be able to compare Norwegian salmon farming companies based on their biodiversity impact performance, we utilize a clustering methodology. By doing this, we help investors, companies, and regulators to collect information, analyze behavior and recognize patterns (Chong et al. 2012) in how Norwegian salmon farming companies impact biodiversity. Several studies have tried to categorize companies based on how well they perform on environmental and sustainability issues by using clustering approaches (Jamali et al. 2009; Afonso et al. 2012; Ortas et al. 2015; Jitmaneeroj 2016; Iamandi et al. 2019; Perchinunno et al. 2020). These studies use different indicators to measure and categorize the companies' sustainability patterns, ranging from ESG-ratings from third-party companies (Jitmaneeroj 2016) to specific sustainability indicators for university campuses (Perchinunno et al. 2020). Afonso et al. (2012) investigate the correlation between firms' social and financial performance, while Iamandi et al. (Iamandi et al. 2019) clusters European companies to uncover insights into the companies' sustainable behaviors. These studies

[6] The standard/document specifies sampling frequency and method for measuring and assessing bottom impact from marine aquaculture facilities. Source: Institute of Marine Research (2016)

commonly use metrics and indicators as a snapshot in time (e.g., ESG-ratings). In this thesis, we apply a clustering methodology to classify and rank Norwegian salmon farming companies based on their biodiversity impact over several years and provide a novel contribution to the literature. Another stream of firm clustering literature examines how companies can be categorized based on time series data (Focardi 2002; Todorovski et al. 2002; Basalto et al. 2007; Piccardi et al. 2011). These studies cluster companies based on financial time series data to find companies with similar behaviors. The data on biodiversity impact variables escapes and bottom condition surveys are of such character that it is unsuitable for time series analysis since the data set's observations are less frequent and have varying time intervals. However, some data sets available for our identified biodiversity impact variables show time-series properties (i.e., lice counts, disease outbreaks, and lice treatments). Therefore, we use time-series clustering methods to check the robustness of our clustering results by using time series data of our developed biodiversity impact indicators. Hence, we also contribute to the literature on categorizing and clustering companies based on time series data and, more specifically, clustering on biodiversity impact indicators to assess Norwegian salmon farming companies‘ biodiversity impact performance.

# 3 Data description

We use publicly available data sets from the Directorate of Fisheries and the Norwegian Food Safety Authority. To the best of our knowledge, we are the first to combine these data sources into one data set to assess Norwegian salmon farming companies' biodiversity impact indicators. The initial sample consists of around 120 companies owning commercial licenses for salmon and trout in Norway, but some of these companies are controlled by other companies. Around 90 companies produce the total supply of salmon in Norway, with 23 of these producing about 80% of the farmed salmon and trout in Norway (Mowi 2021). In this thesis, we focus on the 36 largest salmon farming companies in Norway in terms of slaughter weight in 2020.[7] Table 2 summarizes the primary data sources for the variables we use throughout this thesis and presents basic descriptive statistics for the variables. More detailed descriptive statistics for the different data sets before normalizing are presented in Appendix A. Section 3.1 describes the data cleaning process, starting from the initial data sets for our variables and all the refinement steps towards our final data set. Section 3.2 summarizes the final data set used in our model.

| Biodiversity impact variable | Source | Years | Proxy | Indicator on company level | Mean | Median | SD |
|---|---|---|---|---|---|---|---|
| Escapes | The Directorate of Fisheries | 2016 - 2021 | Number of escaped farmed salmon | Escaped individuals per locality, rolling average last three years | 152,659 | 2,290 | 408,498 |
| Sea lice | The Norwegian Food Safety Authority | 2016 - 2021 | Weekly reported lice counts | Average number of lice per count | 0,100 | 0,104 | 0,081 |
| Lice treatments | The Norwegian Food Safety Authority | 2016 - 2021 | Number of medicinal lice treatments | Number of medicinal lice treatments per locality | 1,273 | 0,879 | 1,752 |
| Diseases | The Norwegian Food Safety Authority | 2016 - 2021 | Confirmed disease outbreaks (ISA and PD) | Annual outbreaks per locality | 0,258 | 0,258 | 0,247 |
| Bottom conditions | The Directorate of Fisheries | 2016 - 2021 | Bottom survey scores | Percentage of bottom survey scores that are 1 or 2 | 88,123 | 89,237 | 12,275 |

Table 2: Definition and stastistics of variables before normalizing.

## 3.1 Data cleaning process

**Escapes**
The Directorate of Fisheries is the source for the data set on escapes, providing data on all confirmed escape incidents from 2014 to today. First, we create a subset of the 300 escape incidents in which the 36 companies we focus on are involved. Then, we aggregate the numbers of individual salmon that have escaped from each farmer each year, before dividing the number of escapees by the number of localities the farmer was registered with that very year. Lastly, the escape count is transformed from an annual number to a rolling average over three years. This is done partly because escaped salmon can affect biodiversity several years after it has escaped, and partly to mitigate some of the influence big singular escape events can have on the escape score. In other words, *the escapes input metric to our model is a rolling average over the number of escapees per locality per year for the three years prior.*

**Sea lice**
A substantial amount of lice count data exists since every locality with salmon in their pens has to report lice data weekly to the Norwegian Food Safety Authority. The data set on lice count from 2016 to 2021 consists of 334 272 observations, downloaded directly from BarentsWatch[8]. When removing observations from localities not belonging to any of the 36 fish farming companies we analyze, the data set consists of 264 541 rows. *The input metric we use for lice counts is the average number of mature female sea lice per counting over a whole calendar year.* To find this metric for every company, we aggregate all the lice count numbers for all the localities connected with the company in a given year and divide it by the number of counts performed by the company that year. If a company runs a locality as a joint venture with another company, the lice number

[7]An overview of slaughter weight for all Norwegian fish farmers with more than six permits was provided for us by Kontali Analyse on November 12, 2021.

[8]BarentsWatch is a Norwegian monitoring and information system for the northern sea and coastal areas launched in 2011. The platform provides updated reported data from the aquaculture industry on escapes, sea lice, diseases and lice treatments (BarentsWatch 2022).

is multiplied by 0,5 for those counts.

**Lice treatments**
We use data from the data set on lice treatments as a proxy for the non-target delousing effect of Norwegian salmon farming companies. The total data set consists of 38 779 observations from 2016 to 2022. After removing the observations belonging to other companies, 17 972 observations are left. The data was downloaded directly from BarentsWatch. Lice treatments are being reported every week on a locality level to the Norwegian Food Safety Authority. The weekly observations state if all pens or only parts of the locality were treated. Since the data does not say how much of the locality was treated in case of a partial treatment, we weigh all observations in the data set equally as one medicinal lice treatment. *The input metric for lice treatments to our model is thus the number of medicinal lice treatments per locality in a given calendar year.*

**Diseases**
The disease data set is downloaded directly from BarentsWatch. The total data set consists of 2477 cases of PD and ISA from 2016 to 2022. First, a subset is created containing only the 1250 confirmed disease cases belonging to a locality where one of the companies within our scope operates. Then, the number of disease cases per company is divided by the number of localities per company. *The input metric to the model is thus the number of disease cases per locality per year.* A company may have more than one disease outbreak per locality per year, as dual outbreaks of PD and ISA might occur, or salmon from different production cycles within a year might suffer from separate disease outbreaks.

**Bottom conditions**
The data set covering bottom survey scores is downloaded directly from the Directorate of Fisheries, which provides two overlapping data sets. "Historical B-surveys" is the most extensive data set, consisting of 7 135 observations from 2008 to 2022, while the second data set, "B-surveys", contains 914 observations from 2019 to 2022. These data sets have zero duplicates, and the reason the data is split like this remains unknown. Survey scores belonging to localities connected to operators other than the 36 companies in our scope were removed from the data set. The final data set for bottom condition surveys consisted of 3 288 observations dating from 2016 to 2021. From these observations, *the percentage of survey scores that were either 1 or 2 for each company for a given year were calculated as input metric.*

**Normalization procedures**
For all the five biodiversity impact indicators, except for escapes, the last step before inputting data to our model is an annual normalization from 0 to 10. The best performing company every year gets a 10, while the worst performing company gets a 0. When normalizing the escape scores to a 0-10-scale for further analysis, we let the most considerable three-year rolling average number globally represent a score of 0. Correspondingly, all fish farmers with zero escapes on their rolling average number get a best-in-class score of 10 for the given year. The reason for handing out a global 0-10-score instead of annual 0-10-scores is that escape numbers have a considerable variability and much fewer observations than the other variables. Hence, singular escape incidents in a given year affect the normalization score to a large degree, making performance comparison difficult. Here, our rolling average method provides a more fair way of comparison.

**Location structure**
In order to map biodiversity impact performance to a specific company, it is necessary to map all localities to the salmon farming companies we focus on in this thesis. This process starts with the Norwegian Aquaculture Registry, where all companies with fish farming activities in Norway are registered with their permits and localities (The Directorate of Fisheries 2022). To systematize the locality structure belonging to the 36 companies in our scope, we need to make some assumptions due to the structure of the data available.

Firstly, the Aquaculture Registry shows a snapshot of the current state of the locality structure.

We therefore extract data on the locality structure per January 1st for all relevant years. Thus, we assume that the Norwegian locality structure per January 1st is a good proxy for the rest of the year. In reality, some localities are likely traded between different companies during the year. It is also likely that some localities are abandoned or established during a year. However, as seen in Appendix B, the number of localities per company is relatively stable on a year-to-year basis. Hence, our assumption that locality structure deviations throughout the year have a negligible effect on our results is credible.

Secondly, the relation between a locality and an operating fish farmer is not always 1-to-1. For some localities, several companies are responsible via their respective permits as joint ventures. From a company perspective, such collaborations make it possible to fully utilize a locality if there is a mismatch between the company's permitted biomass and the maximum permitted biomass of a locality (Hosteland 2014). There is also an element of diversification involved, incentivizing fish farmers to spread their biomass over different localities. Having all biomass in one locality makes the company more vulnerable to e.g. algae blooms or a severe disease outbreak (Karlsen et al. 2019). According to the Norwegian Directorate of Fisheries[9], it is not possible to use the Aquaculture Registry to decide which salmon farming company has the primary responsibility for the operations at a locality related to several companies. The Directorate of Fisheries uses monthly biomass reported from the localities in order to have an overview of who is currently running the operations at each locality. This data is considered financially sensitive and is therefore not publicly available. Hence, we investigate the permits registered on each locality to determine which company has the main responsibility for the operations there. However, the Aquaculture Registry does not say how large a share of the production permits the companies are utilizing on the locality. This makes it challenging to decide which companies are actually responsible for the operations and weigh the biodiversity impact responsibility for the companies having production permits at the locality correctly. Thus, we assume that if a company has more than 80% of the production permits on a locality, it is the main operating company, assigning the locality and all its biodiversity impact measures to the given company with a weight of 1. Concurrently, a fish farming company having less than 20% of a locality's permits is not assigned any of the biodiversity impacts from that locality. For companies with a share of permits on a locality between 20% and 80%, we weight the operators taking part at 0,5 each. These weightings also follow the operating companies when we rate their biodiversity impact performance (i.e., a disease outbreak at a joint venture locality counts as half a disease outbreak for each of the involved companies). The weightings of joint venture localities are summarized in Table 3 below. This way of connecting localities and companies might not always correspond exactly to what the respective companies report in their external reports. However, for the purpose of our biodiversity assessment, we assume that this method provides a sufficient level of detail regarding locality structure, treating all companies equally and fairly.

| **Share of locality permits** | **Weight** |
|---|---|
| $\geq$ 80% | 1 |
| 20% - 80% | 0,5 |
| $\leq$ 20% | 0 |

Table 3: Assigned weight to each fish farmer corresponding to share of permits on a locality.

A third factor to consider in our analysis is that at any given time, between 30% and 40% of localities in Norway are fallowed (Sommerset et al. 2021). Therefore, we assume that over time, all companies have the same share of their locations fallowed. This assumption is plausible as all salmon farming companies have incentives to keep the fallowing periods as short as possible. At the same time, the regulators demand a minimum fallowing period for each generation of fish (Ministry of Trade, Industry and Fisheries 2021a). Thus, we assume that the companies keep their fallowing periods as short as legally possible on their localities to maximize profits.

Summarized, these assumptions regarding the locality structure, joint venture operations and fallowing of localities allow us to fairly compare and investigate the biodiversity impact performances of Norwegian aquaculture companies in a standardized and systematized way.

[9] Interview with an advisor for the Directorate of Fisheries on March 25, 2022.

## 3.2 Final data set

The extensive data cleaning and variable selection processes described above leave us with a data set consisting of 36 companies and 287 294 observations from the five biodiversity impact variables. Table 4 provides an overview of all companies in our data set. Among the 36 companies within our scope, six are publicly traded on Oslo Stock Exchange or Euronext Growth, while the rest are privately owned. It is evident that the companies differ a lot in size, both in terms of slaughter weight in 2020 and the number of localities in Norway. Sulefisk AS only slaughtered 1,4 % of the amount that Mowi ASA slaughtered in 2020, with Mowi's volumes coming from 25 times as many operating localities.

In 2017 the government of Norway introduced a new system for growth in the aquaculture sector, "the traffic light system". The idea is that the key to growth is the sea lice pressure (Olaussen 2018). This means that the sea lice effect on wild salmon mortality is the indicator allowing or disallowing production growth. With this system, the government also divided the Norwegian coastline into 13 production areas. In production areas where sea lice levels cause wild salmon smolt mortality for less than 10% of the regional stock, a green light for increasing production by 6% will be given. A yellow light will be given when sea lice-induced mortality is between 10% and 30%. A yellow light means that the growth is on hold, i.e., constant production. If an area gets a red light, the sea lice-induced mortality is higher than 30%, and production should be reduced (Boxaspen 2020). An overview of the 13 production areas in Norway is shown in Appendix C. In our final data set, only 5 companies operate in more than two production areas, and only 3 operate in more than three production areas, implying that most Norwegian fish farming companies operate in a limited geographic area. The two most geographically diversified companies in terms of localities in Norway are Mowi and Salmar, operating in 10 and 7 production areas, respectively. The last two columns in Table 4 indicate whether the company operates in the southwestern part of Norway or the northern part of Norway. The companies in our data set are evenly split between the two regions. 15 companies are only operating in the southwestern part (production area 1 to 6) and 16 are operating only in the northern part of Norway (production area 7 to 13). Five companies are split between the two regions; Lerøy, Mowi, Salmar, Grieg and Bjørøya. However, as Bjørøya has very few localities in production area 6, all very close to the border between the two regions, we consider all of its localities belonging to the northern production areas.

Table 5 presents the geographical segmentation of the companies and observations in the final data set. We can see that production areas 3, 4 and 10 are the production areas where most companies in our data set are operating. The data set covers all 13 production areas in Norway, with production areas 3, 4 and 6 being the areas most represented, with almost 40% of all localities. The southernmost and northernmost production areas, areas 1 and 13 respectively, are the areas with the lowest activity level. A more detailed description of localities among the companies and in which production areas they operate is shown in Appendix D.

| Company | Slaughter weight [tonnes] | Localities | PA | Private/Publicly traded | South/western PA | Northern PA |
|---|---|---|---|---|---|---|
| Mowi ASA | 262 000 | 147 | 10 | Public | 65 % | 35 % |
| Lerøy Seafood Group ASA | 170 900 | 115 | 6 | Public | 76 % | 24 % |
| Salmar ASA | 147 700 | 83 | 7 | Public | 58 % | 42 % |
| Cermaq Norway AS | 62 700 | 48 | 2 | Private | 0 % | 100 % |
| Grieg Seafood ASA | 46 900 | 38 | 2 | Public | 42 % | 58 % |
| Nova Sea AS | 42 600 | 26 | 1 | Private | 0 % | 100 % |
| Nordlaks Oppdrett AS | 35 000 | 37 | 2 | Private | 0 % | 100 % |
| Alsaker Fjordbruk AS | 31 000 | 22 | 2 | Private | 100 % | 0 % |
| NRS Farming AS | 30 500 | 25 | 3 | Public | 0 % | 100 % |
| Sinkaberghansen AS | 28 700 | 29 | 2 | Private | 0 % | 100 % |
| Salmonor AS | 28 300 | 27 | 1 | Private | 0 % | 100 % |
| Bremnes Seashore AS | 24 400 | 26 | 2 | Private | 100 % | 0 % |
| Eidsfjord Sjøfarm AS | 17 000 | 16 | 3 | Private | 0 % | 100 % |
| Måsøval AS | 16 300 | 13 | 2 | Public | 100 % | 0 % |
| Firda Sjøfarmer AS | 14 000 | 17 | 1 | Private | 100 % | 0 % |
| Blom Fiskeoppdrett AS | 13 100 | 12 | 1 | Private | 100 % | 0 % |
| Eide Fjordbruk AS | 12 500 | 10 | 2 | Private | 100 % | 0 % |
| Erko Seafood AS | 12 500 | 11 | 2 | Private | 100 % | 0 % |
| Bolaks AS | 11 600 | 21 | 1 | Private | 100 % | 0 % |
| Bjørøya AS | 10 900 | 21 | 2 | Private | 19 % | 81 % |
| Ellingsen Seafood AS | 10 400 | 10 | 1 | Private | 0 % | 100 % |
| Hofseth Aqua AS | 9 500 | 6 | 1 | Private | 100 % | 0 % |
| Lingalaks AS | 9 000 | 12 | 2 | Private | 100 % | 0 % |
| Lovundlaks AS | 9 000 | 9 | 1 | Private | 0 % | 100 % |
| Flakstadvåg Laks AS | 8 400 | 8 | 1 | Private | 0 % | 100 % |
| Emilsen Fisk AS | 8 100 | 15 | 1 | Private | 0 % | 100 % |
| Tombregruppa | 7 600 | 11 | 2 | Private | 100 % | 0 % |
| Osland Havbruk AS | 7 500 | 7 | 1 | Private | 100 % | 0 % |
| Egil Kristoffersen og Sønner AS | 7 000 | 10 | 1 | Private | 0 % | 100 % |
| Wilsgård Fiskeoppdrett AS | 7 000 | 9 | 2 | Private | 0 % | 100 % |
| Kobbevik og Furuholmen Oppdrett AS | 6 800 | 7 | 2 | Private | 100 % | 0 % |
| Kleiva Fiskefarm AS | 6 500 | 11 | 1 | Private | 0 % | 100 % |
| Gildeskål Forskningsstasjon AS | 6 400 | 8 | 2 | Private | 0 % | 100 % |
| Steinvik Fiskefarm AS | 6 300 | 9 | 1 | Private | 100 % | 0 % |
| Salaks AS | 5 000 | 9 | 1 | Private | 0 % | 100 % |
| Sulefisk AS | 3 600 | 6 | 1 | Private | 100 % | 0 % |

Table 4: Overview of the final set of Norwegian fish farming companies analyzed in this thesis. Slaughter weight equals metric tonnes slaughtered in 2020. Localities is the number of localities the company operated (or partly operated) at the end of 2021. PA is the number of production areas the company operates in. The last columns are the share of a company's locations in the southwestern production areas (PA 1-6) versus the northern production areas (PA 7-13). Sources: BarentsWatch (2022), Kontali Analyse and Oslo Euronext (2022b) and Oslo Euronext Growth (2022a)

| Production zone | Operating companies | Localities | Observations |
|---|---|---|---|
| 1 | 1 | 5 | 2 412 |
| 2 | 4 | 45 | 16 029 |
| 3 | 9 | 129 | 40 797 |
| 4 | 12 | 109 | 37 099 |
| 5 | 6 | 38 | 12 849 |
| 6 | 5 | 114 | 38 475 |
| 7 | 6 | 103 | 28 782 |
| 8 | 5 | 69 | 23 393 |
| 9 | 7 | 82 | 26 839 |
| 10 | 9 | 91 | 22 623 |
| 11 | 5 | 19 | 12 327 |
| 12 | 4 | 72 | 22 152 |
| 13 | 2 | 15 | 4 514 |
| Total | | 891 | 28 8291 |

Table 5: Geograhical segmentation of observations and the companies in our final data set for 2021. Source: BarentsWatch (2022)

# 4 Model

One of the challenges when it comes to systematizing our data set into a common rating methodology is the relative importance of the variables used. The assignment of weights to the different variables is subjective, as different metrics are of different importancy to different stakeholders. To meet this challenge, we utilize the unsupervised K-means clustering algorithm as a vital part of our model, where assignment of weights to the input variables is not necessary. The intuition behind K-means clustering is to minimize the Euclidean distance between nodes in the same cluster and maximize the euclidean distance to nodes in other clusters. This way, the final clusters can be used to identify nodes - in our case salmon farming companies - with similar biodiversity impact performance. Mathematically, the algorithm initializes cluster centroids randomly as in Equation 1, and then the steps in Equation 2 are repeated until convergence.

$$\mu_1, \mu_2, \mu_3, ..., \mu_k \in \mathbb{R}^n \tag{1}$$

$$\begin{aligned} \{ \ \forall i \in \{1, m\} \ \ c^{(i)} &:= \arg\min_j ||x^{(i)} - \mu_j||^2 \\ \forall j \in \{1, k\} \ \ \mu_j &:= \frac{\sum_{i=1}^m 1\{c^{(i)} = j\} x^{(i)}}{\sum_{i=1}^m 1\{c^{(i)} = j\}} \ \ \} \end{aligned} \tag{2}$$

For every year in our data from 2016 to 2021, we collect company performances on our five biodiversity impact variables: escapes, sea lice, diseases, lice treatments and bottom surveys. Each company is compared to its peers annually before its performance is scaled from 0 to 10. The best-in-class on each biodiversity metric gets a rating of 10, while the worst-in-class gets a 0. After that, the K-means clustering algorithm minimizes the distance between the biodiversity scores of the different fish farmers, aiming to place the most similar performing companies in the same cluster. Finally, we rank the clusters according to the average biodiversity scores of the companies within each cluster. An overview of our model is shown in Figure 1 below.

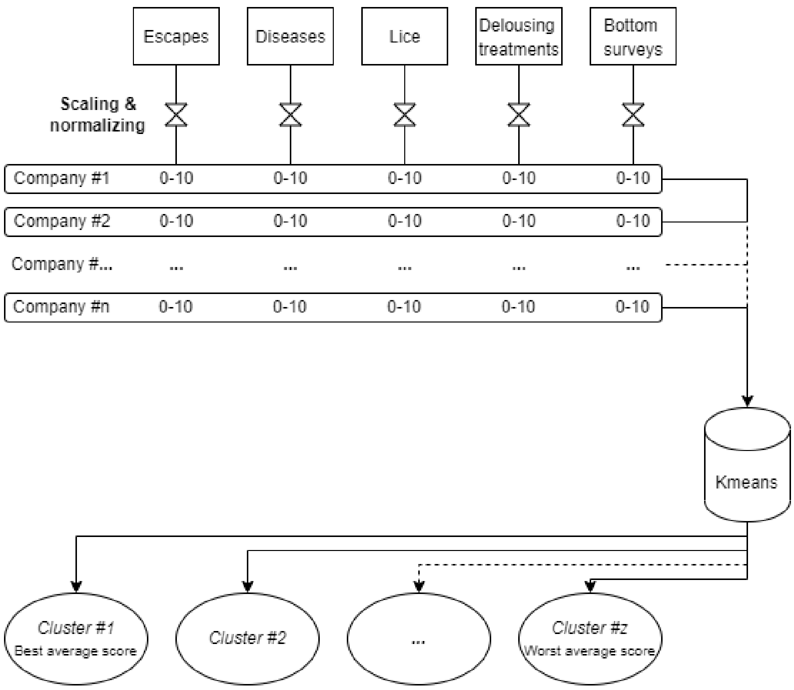


Figure 1: Illustration of our application of the K-means algorithm. For every year in the dataset, we utilize K-means to place the companies in 4 different clusters based on their biodiversity impact performance.

The annual cluster distribution is then used to rank the companies over a longer timeframe than a sole year. In order to rank the best biodiversity impact performers over a six year period, we sum up the number of times a company ended up in different clusters as shown in Figure 2. This way, if a company ended up in the best cluster all six years, it gets a score of $1+1+1+1+1+1=6$. A lower score is better, meaning that the company achieving the lowest score in this part of the model is the overall best biodiversity performer. We use $K=4$ for all clustering approaches in this thesis since 4 is among the K's achieving the best silhouette scores. It also provides enough clusters to separate between companies while keeping relatively many companies in each cluster. With $K=4$, the best possible score is 6 - ending up in the best cluster, 1, all years. The worst possible score is 24, ending in the worst cluster, 4, all years from 2016 to 2021. The clusters may be classified according to their characteristics and the identification variables considered:

- Cluster 1: "Top biodiversity impact performers" are among the best performers on our selected variables.
- Cluster 2: "High biodiversity impact performers" with a medium level of impact performance.
- Cluster 3: "Medium biodiversity impact performers" with a medium to low level of impact performance.
- Cluster 4: "Low biodiversity impact performers" which perform much poorer than other companies on our selected variables.

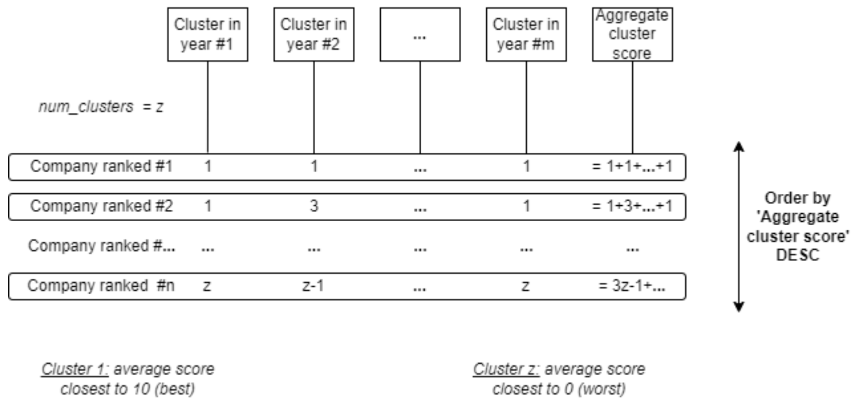


Figure 2: Illustration of ranking procedure scoping m years. We aggregate a cluster score from all years and order the companies descending based on the aggregated biodiversity impact scores.

# 5 Results and Discussion

This section is structured as follows. Section 5.1 presents our results on our biodiversity impact ranking nationwide and on singular biodiversity impact variables. We also present and discuss our results when splitting the data set between southwestern and northern production areas in Norway. Section 5.2 investigates how the four largest listed salmon farming companies in Norway perform compared to each other. Finally, section 5.3 presents a robustness check of our model by employing univariate time series clustering.

## 5.1 Model results

To investigate and categorize the biodiversity impact footprint of aquaculture companies in Norway, we first perform a nationwide comparison between the 36 biggest salmon farming companies. Thus, we run through our model illustrated in Figure 1 and Figure 2, including all our five biodiversity impact variables in a multivariate clustering framework. Each company gets classified into a cluster yearly based on its biodiversity impact performances. Aggregating the cluster placement scores over the period from 2016 to 2021 results in the biodiversity impact ranking of each salmon farming company. Figure 3 below illustrates how many companies end up in each cluster each year following our model. Cluster 1 - the best cluster - is the most populated, with approximately 40% of the companies on average. Looking at the other side of the ranking, we see that cluster 4 is the least populated, occasionally with as few as one or two companies.

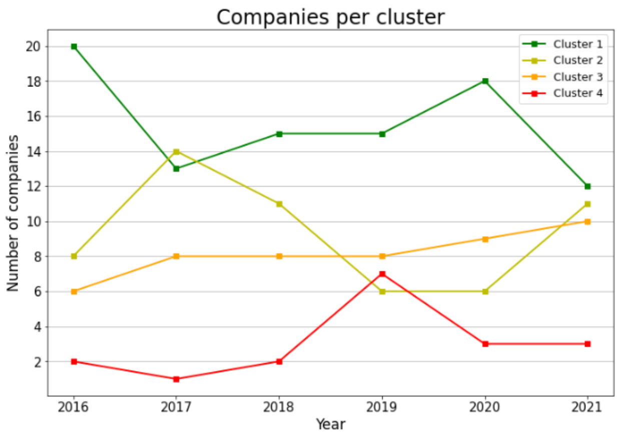


Figure 3: Number of companies per cluster per year.

In Figure 4, the nationwide development of cluster scores for cluster 1 and 4 are compared. While the cluster averages for cluster 1 consequently stay above a score of 6, both overall and for the different variables, the cluster averages of cluster 4 are much more volatile. Several variables stay below an average score of 6 most of the years, especially diseases, which only scored better than 6 in 2018. It is also evident that the escape numbers are different from the rest of the variables. In 2016 and 2017, companies in cluster 4 were negatively affected by rather large escape incidents. For the years after 2017, the companies in cluster 4 achieve a close to perfect score on escapes, emphasizing how variable the escape numbers are.

The development of average cluster scores on the five variables, including the overall average score, is presented in Figure 5 below. We see that cluster 1 performs better and is more consistent than the other clusters. However, it performs worse than other clusters on lice treatments and escapes, which indicate that these variables affect the overall score less than other variables. In 2019 and 2020, the overall scores for all four clusters are relatively close together. There are several reasons for this; firstly, cluster 1 has a bad year on bottom surveys in 2019, and companies in cluster 2 and 4 have an excellent lice year in 2020. Simultaneously, cluster 4 includes more companies these years than the prior years, as visible in Figure 3, leading to the cluster 4 averages being less

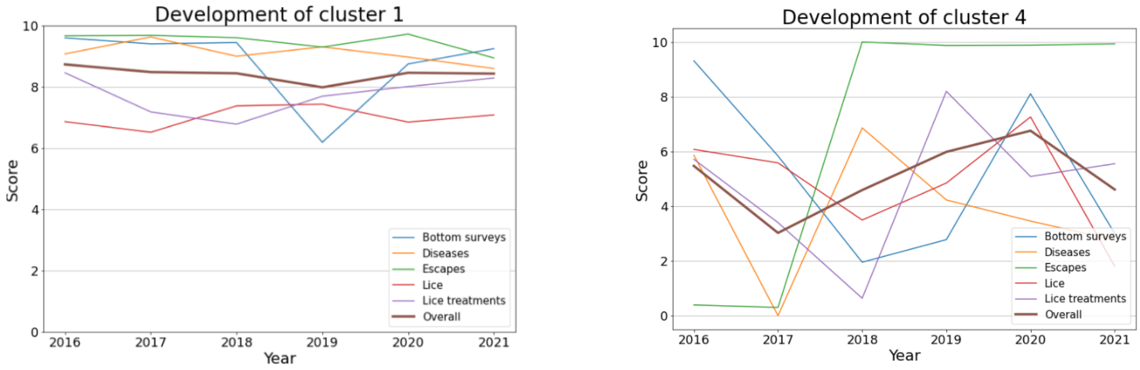


Figure 4: Comparison of cluster 1 and cluster 4 from 2016-2021.

dominated by companies with a poor year on a given variable. It can also be seen that the variables where cluster 4 performs worst compared to the other clusters are bottom conditions and diseases. However, in some years (i.e., 2019 and 2020), cluster 4 performs as well as the other clusters on lice and lice treatments. It is evident that the average normalized scores on the variables for all clusters except cluster 1 vary a lot from one year to another, while the scores for cluster 1 is more stable over the years. We see that the escape variable is behaving different than the other variables, as in 2016 and 207, where large escape incidents is dragging down the average overall score for cluster 4 while the other clusters perform well. The reason for this is that escape incident occur relatively rarely and with a varying number of escaped salmon per incident, but once a big incident occur it affects the normalized score to a large degree. The normalized cluster scores for lice are generally lower than for the rest of the variables, even for cluster 1 where the average score never exceeds 8, indicating that it is difficult to achieve high company scores on sea lice counts.

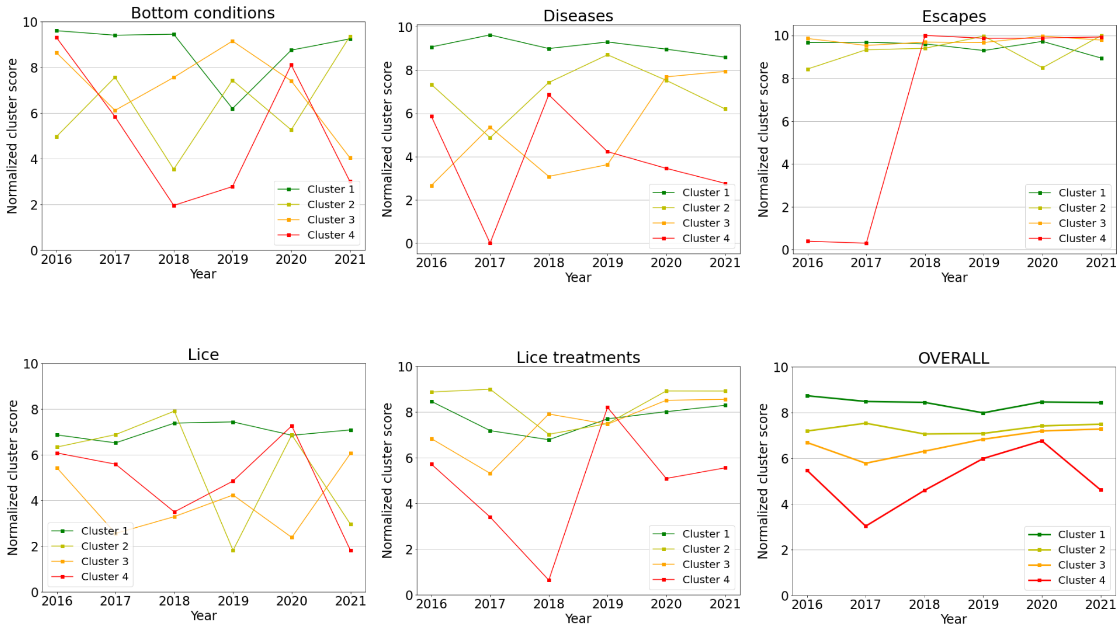


Figure 5: Development of average cluster scores on the different variables from 2016 to 2021. The "OVERALL" line diagram is simply the average of the other five line diagrams.

The clusters described so far in this section result in the overall ranking presented in Table 6 below. Five salmon farming companies end up in cluster 1 all years; Wilsgård Fiskeoppdrett, Nova Sea, Cermaq Norway, Kleiva Fiskefarm and Gildeskål Forskningsstasjon. On the other side of the rankings, three companies stand out negatively. Eide Fjordbruk, Blom Fiskeoppdrett and Sulefisk are ranked last with scores of 19 and 20, averaging a cluster placement of 3.2 and thus the companies that end up in cluster 4 most often. The full ranking table is presented in Appendix E.

| Rank | Company | Total score |
|---|---|---|
| *1* | Cermaq Norway AS | 6 |
| *1* | Gildeskål Forskningsstasjon AS | 6 |
| *1* | Kleiva Fiskefarm AS | 6 |
| *1* | Nova Sea AS | 6 |
| *1* | Wilsgård Fiskeoppdrett AS | 6 |
| ... | ... | ... |
| *34* | Sulefisk AS | 19 |
| *35* | Blom Fiskeoppdrett AS | 19 |
| 36 | Eide Fjordbruk AS | 20 |

Table 6: Overall nationwide rating. Input data is all five biodiversity factors annually from 2016 to 2021.

After establishing the nationwide overall ranking in Table 6, we zoom in on the different input factors to get insights into the contributions of individual biodiversity impact variables to the overall ranking. We therefore run our model illustrated in Figure 1 and Figure 2 for each of our biodiversity impact variables separately. From this, we see which companies performed best among the 36 largest salmon farming companies in Norway on each of our biodiversity impact variables in the period from 2016 to 2021. Below, in Table 7, 8, 9, 10 and 11, the top and worst performers on each biodiversity impact variable is shown.

| Rank | Company | Escape score |
|---|---|---|
| *1* | Egil Kristoffersen & Sønner | 6 |
| *1* | Ellingsen Seafood AS | 6 |
| *1* | Erko Seafood AS | 6 |
| *1* | Flakstadvåg Laks AS | 6 |
| *1* | Gildeskål Forskningsstasjon | 6 |
| *1* | Kleiva Fiskefarm AS | 6 |
| *1* | Kobbevik og Furuholmen | 6 |
| *1* | Måsøval AS | 6 |
| *1* | NRS Farming AS | 6 |
| *1* | Osland Havbruk AS | 6 |
| *1* | Salaks AS | 6 |
| *1* | Steinvik Fiskefarm AS | 6 |
| *1* | Sulefisk AS | 6 |
| ... | ... | ... |
| *35* | Sinkaberghansen AS | 15 |
| *36* | Bjørøya AS | 16 |

Table 7: Nationwide best and worse on *escapes*. Full table in Appendix F.

| Rank | Company | Licecount score |
|---|---|---|
| *1* | Wilsgård Fiskeoppdrett AS | 6 |
| *2* | SinkabergHansen AS | 7 |
| *3* | Cermaq Norway AS | 8 |
| ... | ... | ... |
| *34* | Blom Fiskeoppdrett AS | 22 |
| *35* | Erko Seafood AS | 23 |
| *35* | Firda Sjøfarmer AS | 23 |

Table 8: Nationwide best and worse on *sea lice*. Full table in Appendix G.

| Rank | Company | Disease score |
|---|---|---|
| *1* | Cermaq Norway AS | 6 |
| *1* | Egil Kristoffersen & Sønner | 6 |
| *1* | Eidsfjord Sjøfarm AS | 6 |
| *1* | Ellingsen Seafood AS | 6 |
| *1* | Flakstadvåg Laks AS | 6 |
| *1* | Kleiva Fiskefarm AS | 6 |
| *1* | Lovundlaks AS | 6 |
| *1* | Nordlaks Oppdrett AS | 6 |
| *1* | Nova Sea AS | 6 |
| *...* | ... | ... |
| *34* | Hofseth Aqua AS | 20 |
| *35* | Erko Seafood AS | 20 |
| *36* | Kobbevik og Furuholmen | 21 |

Table 9: Nationwide best and worse on *diseases*. Full table in Appendix H.

| Rank | Company | Bottom conditions |
|---|---|---|
| *1* | Kobbevik og Furuholmen | 6 |
| *1* | Hofseth Aqua AS | 6 |
| *1* | Gildeskål Forskningsstasjon | 6 |
| *1* | Flakstadvåg Laks AS | 6 |
| *...* | ... | ... |
| *35* | Blom Fiskeoppdrett | 20 |
| *36* | Lingalaks | 21 |

Table 10: Nationwide best and worse on *bottom conditions*. Full table in Appendix I.

| Rank | Company | Lice treatments |
|---|---|---|
| *1* | Lerøy Seafood Group ASA | 6 |
| *1* | Tombregruppa | 6 |
| *1* | Måsøval AS | 6 |
| *...* | ... | ... |
| *34* | Eide Fjordbruk AS | 19 |
| *35* | Gildeskål Forskningsstasjon | 19 |
| *36* | Osland Havbruk AS | 22 |

Table 11: Nationwide best and worse on *lice treatments*. Full table in Appendix J.

The tables above highlight which variables affect the overall nationwide ranking for some of the worst and best-ranked companies on biodiversity impact performance. For example, we see that Blom Fiskeoppdrett AS is ranked among the bottom performers both on lice in Table 8 and bottom conditions in Table 10. Based on this, it makes sense that they are also ranked among the worst biodiversity impact performers nationwide. Looking at Table 11, it is plausible that Eide Fjordbruk AS is placed among the bottom performers nationwide partly due to their performance on lice treatments. Looking at the five top-performing companies on the nationwide ranking, all are on top of the list in at least one of the singular biodiversity impact variable rankings. Among the companies standing out in the overall nationwide ranking, Sulefisk AS is the only exception - not ending up among the worst performers on any of the singular variable ratings, even though they are ranked among the worst overall. This indicates that their poor overall biodiversity impact ranking most likely results from a stable poor performance on all the singular variables.

Among the salmon farming companies in our data set, Mowi, Lerøy, Grieg and Salmar have the most diversified locality structures spread over several production zones in both north and south of Norway as shown in Table 4. Out of these companies, Lerøy is the only one among the best or worst performing companies in any of the singular biodiversity impact variable rankings through their top performance on lice treatments in Table 11. The lack of diversified companies standing out could have something to do with their locality structure. Most smaller salmon farming companies operate in a limited geographic area of Norway (as discussed in Section 3.2), leaving them exposed to biodiversity impact risks out of management control. Sea water temperature and locality density in the area they operate in is out of the management's hand to deal with, even though it increases the risk of high sea lice levels and disease outbreaks (Godwin et al. 2020; Oliveira et al. 2021). The diversified companies have a broader exposure to these non-managerial biodiversity impact risks, which could explain why they do not stand out in the nationwide comparison.

Regarding the singular biodiversity impact variable rankings for sea lice and diseases in Tables 8 and 9, all the top-performing aquaculture companies operate solely in the north as seen in Table 4. Oppositely, all the worst performers on diseases and lice operate solely in the southern and western parts of Norway. In Figure 6, we present the cluster distributions from our model run on the singular biodiversity impact variables, highlighting how large share of companies in the clusters that operate in the southwestern areas or the northern areas of Norway. We see that some biodiversity impact variables indeed are influenced by geography. The cluster distribution between the northern and southern production areas for lice, diseases and overall are way more skewed than those for escapes, bottom surveys and lice treatments. In other words, the nationwide ranking of Norwegian salmon farming companies has a bias from the lice and disease scores when calculating their overall biodiversity impact score.

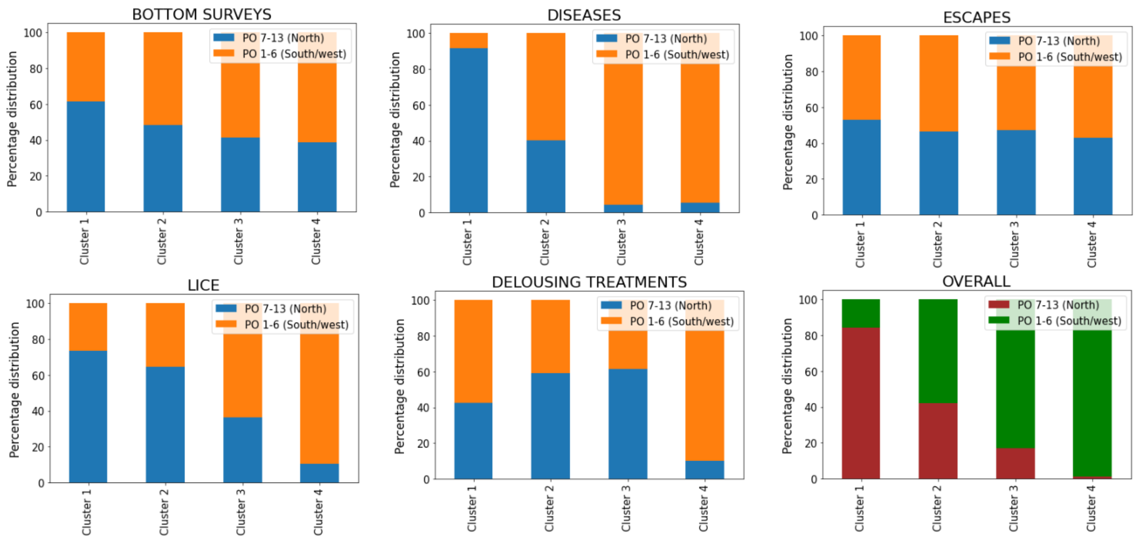


Figure 6: Cluster distribution with regards to geography.

Figure 7 shows a correlation matrix highlighting relations between the singular rankings, the overall ranking, slaughter weight and share of localities in the north or south corresponding to the map. The input data to the correlation matrix can be seen in Appendix K. We find strong correlations between singular rankings and the share of localities in the north/south. For companies operating in the north, there is a negative correlation with diseases, lice numbers and overall score. For companies with their operations in the south - the opposite is observed. In the nationwide overall biodiversity impact ranking, as shown in Table 6 and in detail in Appendix E, the top ten operators have localities exclusively in the seven northernmost production areas. Concurrently, the ten worst biodiversity impact performers have localities solely in the six southernmost production zones. These results indicate that the overall nationwide ranking is strongly influenced by performance on diseases and lice. We see that operating in the south, as shown in Figure 6 and Figure 7, correlates with poor biodiversity impact cluster scores on diseases and lice numbers. This indicates that salmonid farmers operating in the northern production areas have an advantage regarding biodiversity impact performance when our model is applied nationwide.

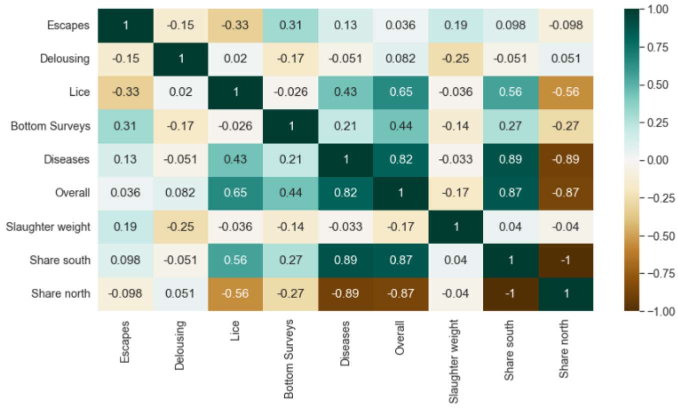


Figure 7: Correlation between ranking on singlar factors, overall ranking, slaughter weight in 2020 and share of localities in north/south.

To further examine these correlations and findings, we perform a regression analysis to see how individual scores on the biodiversity variables affect the overall biodiversity score. We run the regression by using the data table showed in Appendix K. The dependent variable is the "Overall clustering score", while the independent variables are all the singular variable clustering scores in addition to "Slaughter weight 2020" (in 1000 tonnes) and a dummy variable stating if the company has the most of their localities in south/western part of Norway or the northern part. The results from this regression are presented in Table 12 below.

| | Overall clustering score |
|---|---|
| Escapes | -0,023<br>(0,101) |
| Lice treatments | 0,121<br>(0,075) |
| Lice counts | $0,410^{***}$<br>(0,066) |
| Bottom Surveys | $0,423^{***}$<br>(0,064) |
| Diseases | $0,263^{**}$<br>(0,098) |
| Slaughter weight 2020 | $0,011^{*}$<br>(-0,011) |
| South/west | $2,245^{*}$<br>(1,113) |
| Observations | 36 |
| $R^2$ | 0,928 |

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 12: Association between overall biodiversity clustering score and the other biodiversity variables. Standard deviation is shown within the parentheses. Slaughter weight in 1000 tonnes.

From Table 12 we can see that being in the best cluster on lice counts or bottom surveys is positively associated with the overall clustering score and that this effect is statistically significant at the 1% level. It can also be seen that diseases are positively associated with the overall clustering score and that this effect is statistically significant at the 5% level. Together, these three biodiversity impact variables are the most important variables explaining the nationwide overall biodiversity impact performance comparison. The $R^2$ of 0,928 indicates that explanatory variables capture substantial parts of the variation in the overall clustering score.

Table 12 also shows that escapes and lice treatments do not explain the variation in the overall clustering scores well. We also see that lice treatments are a poor variable to explain the overall biodiversity clustering score. This makes sense since we can see that many companies performing well on lice treatments in Table 11 perform relatively poorly on the overall nationwide clustering score as seen in Appendix E. Also, lice treatment methods are more of a management decision than the other biodiversity impact variables, thus also more independent of geographical location than the variables sea lice and diseases. It can also be seen that Gildeskål Forskningsstasjon AS is placed second last on the singular lice treatments ranking in Table 11, while it is ranked as the best on overall biodiversity impact performance in Table 6. This inconsistency is another indicator pointing towards other biodiversity factors being more important for the overall biodiversity impact performance ranking than lice treatments.

It is also evident that slaughter weight has some effect on the overall clustering score, as it is statistically significant at the 10% level, indicating that bigger companies get slightly worse biodiversity impact scores than smaller companies when compared nationwide. Lastly, we see that the coefficient of the dummy variable south/west indicates that if a company is located mainly in the southern or western regions of Norway, it will have a disadvantage compared to if it was operating in the northern parts of Norway. This observation coincides with our already mentioned findings from the correlation matrix in Figure 7, that the geographic location of a fish farming company‘s operations affects the overall scores to a large extent.

The finding of a geographical (dis)advantage among salmon farming companies in Norway are reasonable, given that localities in the north are dispersed over a bigger area than in the south, hence resulting in a lower locality density (Øystese et al. 2021). Due to a lower density of localities, salmon farming companies operating in the north are less vulnerable to contamination and transfer of disease and sea lice between localities. Simultaneously, northern waters are colder, meaning the sea lice propagate slower than in areas with warmer sea water (Godwin et al. 2020). Much due to these factors, the two northernmost counties of Norway have a bigger standard size for a fish farming permit; at 945 tonnes in Troms and Finnmark compared to 780 tonnes elsewhere (Ministry of Trade, Industry and Fisheries 2013b). The north vs. southwest advantage is also reflected in the government's classification of disease zones,[10] in which the 7 northernmost production areas are classified as PD surveillance zones, while 5 out of the 6 southernmost production areas are classified more severely as PD zones (Ministry of Trade, Industry and Fisheries 2017).

Following the findings above, it is clear that companies with localities in the southwestern production areas have a natural disadvantage. Thus, we split the data set as shown in Appendix C, by drawing a line where production areas 6 and 7 meet. Then, we use the same ranking methodology as earlier for the seven northernmost production areas and the six southernmost areas separately. This way, we compare our 36 aquaculture companies' impact performance against other companies facing similar geographic biodiversity impact challenges. Our data set split results in other companies performing best and worst on biodiversity impact performance than for the nationwide comparison. The ranking table for the companies operating in the southwestern production areas is presented in Table 13 and Table 14 for the companies operating in the northern production areas.

Comparing Table 13 to the nationwide biodiversity impact rating in Table 6, we again see Blom Fiskeoppdrett, Sulefisk and Eide Fjordbruk among the worst-rated salmon farming companies. We simultaneously find that the large listed companies Mowi, Salmar, NRS, Lerøy, Måsøval and Grieg Seafood perform well compared to the privately owned salmon farming companies operating in the same region. These six companies end up among the top nine biodiversity impact performers operating in the southwestern areas of Norway out of 20 companies. Our results on the split data set coincide with the FAIRR Initiative (FAIRR Initiative 2022) Protein Producer Index, as Mowi is the best performing, closely followed by Lerøy Seafood. However, for Grieg Seafood, this is not the case, as Grieg is the second-best performer in the Protein Producer Index, while it is ranked 9th and 10th best performer in the two rankings for the split data set. The deviation of results for some companies is most likely that we utilize a different ranking methodology (i.e., clustering approach on specific biodiversity impact variables) and use other data sources than the FAIRR

[10] A PD zone is established where the PD disease already has a significant presence, aiming to prevent additional contamination and reduce the consequences of the disease. In a PD-surveillance zone, however, the aim is to deny the PD disease a foothold through increased monitoring of fish in the localities to be able to quickly act if the disease has spread from the PD-zone (Mattilsynet 2017).

Initiative. They include general ESG-metrics and depend on company disclosures compared to our usage of data provided by authorities and focus on specific biodiversity impact variables.

A potential explanation for larger companies performing well in the split data set is that they have better routines due to a more extensive base of experience and resources or simply focus on sustainability to attract investors. Also, to grow in terms of getting new production licenses, the salmon farming companies have to perform well on biodiversity impact issues. The Norwegian government prioritizes sustainability and biodiversity matters when granting production permissions to companies (Ministry of Trade, Industry and Fisheries 2021b). Several of the listed fish farmers also have experiences from fish farming in other nations, which might give them an advantage in developing an internal best practice (Mowi Scotland 2022). Another reason could be that the listed players benefit from synergies in consolidations, where knowledge from what was several companies now forms a joint, mutual knowledge base. In this case, better routines, increased focus on biodiversity and more resources could be utilized when acquiring one of the smaller privately-owned companies (Mowi 2021).

| **Rank** | **Company** | **2016** | **2017** | **2018** | **2019** | **2020** | **2021** | **Total** |
|---|---|---|---|---|---|---|---|---|
| *1* | Mowi ASA | 1 | 1 | 1 | 1 | 1 | 2 | 7 |
| *2* | Salmar Farming AS | 1 | 1 | 1 | 2 | 1 | 2 | 8 |
| *3* | NRS Farming AS | 2 | 1 | 2 | 1 | x | x | 9(est.) |
| *4* | Lerøy Seafood Group ASA | 1 | 1 | 2 | 2 | 1 | 2 | 9 |
| *5* | Måsøval AS | 1 | 1 | 1 | 1 | 3 | 2 | 9 |
| *6* | Kobbevik og Furuholmen AS | 1 | 1 | 1 | 2 | 1 | 3 | 9 |
| *7* | Tombregruppa | 1 | 1 | 2 | 3 | 2 | 1 | 10 |
| *8* | Hofseth Aqua AS | 3 | 1 | 1 | 2 | 1 | 2 | 10 |
| *9* | Grieg Seafood ASA | 1 | 2 | 1 | 1 | 3 | 2 | 10 |
| *10* | Bremnes Seashore AS | 1 | 2 | 2 | 3 | 1 | 2 | 11 |
| *11* | Alsaker Fjordbruk AS | 1 | 1 | 1 | 3 | 3 | 2 | 11 |
| *12* | Lingalaks AS | 2 | 2 | 2 | 3 | 2 | 1 | 12 |
| *13* | Bolaks AS | 3 | 1 | 2 | 2 | 2 | 2 | 12 |
| *14* | Steinvik Fiskefarm AS | 1 | 2 | 4 | 3 | 2 | 2 | 14 |
| *15* | Firda Sjøfarmer AS | 4 | 1 | 3 | 1 | 3 | 2 | 14 |
| *16* | Eide Fjordbruk AS | 4 | 4 | 1 | 3 | 2 | 1 | 15 |
| *17* | Erko Seafood AS | 3 | 3 | 3 | 1 | 3 | 2 | 15 |
| *18* | Sulefisk AS | 1 | 2 | 4 | 1 | 3 | 4 | 15 |
| *19* | Blom Fiskeoppdrett AS | 2 | 2 | 3 | 3 | 3 | 4 | 17 |
| *20* | Osland Havbruk AS | 1 | 3 | 1 | 4 | 4 | 4 | 17 |

Table 13: Biodiversity impact performance cluster placement in a given year for southwestern production areas (PA 1-6). Note that NRS Farming sold its localities in the southwestern production areas after 2019, leaving them without a score for the last two years in the dataset.

Table 14 below shows that also in the northern production areas, the listed salmon farming companies perform well. Although not as clearly as in Table 13 for the southwestern production areas, the northern operations of the five listed companies Mowi, Lerøy, Salmar, NRS Farming and Grieg Seafood all get placed in the top half of the biodiversity impact performance ranking out of 21 companies. Again, we see that Cermaq Norway is ranked first, similar to the nationwide ranking, followed by Wilsgård Fiskeoppdrett and Nova Sea. However, the other two top-performing companies from the nationwide ranking, Kleiva Fiskefarm and Gildeskål Forskningsstasjon, does not end up among the top biodiversity impact performers when compared to their peers operating in the northern production areas. This likely results from poor performance on lice and disease management relative to the other salmon farming companies operating in the northern production areas.

| Rank | Company | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | Total |
|---|---|---|---|---|---|---|---|---|
| *1* | Mowi ASA | 3 | 1 | 1 | 1 | 1 | 1 | 8 |
| *2* | Cermaq Norway AS | 2 | 1 | 2 | 1 | 1 | 1 | 8 |
| *3* | Lerøy Seafood Group ASA | 2 | 1 | 3 | 1 | 1 | 1 | 9 |
| *4* | Wilsgård Fiskeoppdrett AS | 1 | 2 | 2 | 1 | 2 | 1 | 9 |
| *5* | Salmar Farming AS | 2 | 1 | 3 | 1 | 2 | 1 | 10 |
| *6* | Nova Sea AS | 3 | 1 | 1 | 1 | 3 | 1 | 10 |
| *7* | Flakstadvåg Laks AS | 1 | 2 | 1 | 2 | 3 | 1 | 10 |
| *8* | Lovundlaks AS | 3 | 1 | 1 | 1 | 1 | 3 | 10 |
| *9* | Nordlaks Oppdrett AS | 3 | 1 | 1 | 2 | 1 | 3 | 11 |
| *10* | NRS Farming AS | 2 | 1 | 2 | 1 | 2 | 3 | 11 |
| *10* | Grieg Seafood ASA | 2 | 1 | 2 | 1 | 2 | 3 | 11 |
| *12* | Ellingsen Seafood AS | 3 | 1 | 1 | 2 | 4 | 1 | 12 |
| *13* | Kleiva Fiskefarm AS | 1 | 1 | 1 | 2 | 3 | 4 | 12 |
| *14* | Salmonor AS | 3 | 3 | 1 | 3 | 2 | 1 | 13 |
| *15* | SinkabergHansen AS | 1 | 3 | 3 | 4 | 1 | 2 | 14 |
| *16* | Eidsfjord Sjøfarm AS | 3 | 1 | 3 | 1 | 3 | 3 | 14 |
| *17* | Gildeskål Forskningsstasjon AS | 1 | 2 | 2 | 2 | 3 | 4 | 14 |
| *18* | Emilsen Fisk AS | 2 | 3 | 4 | 3 | 2 | 1 | 15 |
| *19* | Bjørøya AS | 4 | 3 | 1 | 3 | 3 | 1 | 15 |
| *20* | Egil Kristoffersen & Sønner AS | 3 | 4 | 3 | 1 | 1 | 3 | 15 |
| *21* | Salaks AS | 3 | 1 | 3 | 3 | 2 | 4 | 16 |

Table 14: Biodiversity impact performance cluster placement in a given year for northern production areas (PA 7-13).

We do an ordinary least square regression analysis on the scores from both the southwestern and northern operating companies. The results from the two regression analysis results are presented in Table 15 for the salmon farming companies operating in the southwestern production areas and in Table 14 for the companies operating in the northern production areas. The input data for these regression analyses can be seen in detail in Appendix L and M. The results show that other biodiversity impact variables affect the overall biodiversity impact score regionally than from the regression analysis on the nationwide comparison in Table 12. When splitting the data set, we see that the sign on the "Slaughter weight 2020" coefficient switches to negative for both regressions, indicating that larger companies perform better than smaller companies. A lower score means better performance within our ranking methodology. This change of sign is mainly due to the larger, more geographically diversified companies' performances being dragged down by their localities in the southwestern productions areas when the companies are compared nationwide. Thus, when their performance in the southwestern and northern regions is only compared with companies operating in the same regions, they perform well on biodiversity impact performance.

From the regression on the southwestern operating companies in Table 15, we see that the biodiversity impact variables lice treatments, lice counts and bottom surveys are major contributors to the overall biodiversity impact performance ranking, all statistically significant at the 1% level. These results are slightly different from the regression results nationwide, as the variable lice treatments affect the overall score more in the analysis for the southwestern operating companies than for the nationwide analysis. Similarly, the diseases-variable influence the overall biodiversity impact score for the southwestern operating companies less than in the nationwide regression analysis. These altered influences indicate that many companies in the southwestern areas perform equally on diseases and vary to a large degree internally on lice treatment method performance. Consistent with the nationwide regression analysis in Table 12, lice counts and bottom surveys still affect the overall score significantly for the southwestern operating companies, but roughly half as much based on the coefficients. Overall, this indicates that companies operating in the southwestern production areas should mainly focus on improving their biodiversity impact performance score on lice treatments, lice counts and bottom surveys in order to improve their overall biodiversity impact score when compared to their peers in the southwest.

| | Overall clustering score in southwestern production areas |
|---|---|
| Escapes | 0,176<br>(0,105) |
| Lice treatments | $0,422^{***}$<br>(0,065) |
| Lice counts | $0,284^{***}$<br>(0,069) |
| Bottom surveys | $0,250^{***}$<br>(0,067) |
| Diseases | 0,063<br>(0,083) |
| Slaughter weight 2020 | $-0,019^{**}$<br>(0,006) |
| Observations | 19 |
| $R^2$ | 0,921 |

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 15: Association between overall biodiversity clustering score in production areas 1-6 and the other biodiversity variables for the same areas. The standard deviation is shown within the parentheses. Slaughter weight in 1000 tonnes.

The results from the regression analysis applied to the companies operating in the northern production in Table 16 below show different results than the analysis for the companies operating in the southwest. Our results show that lice treatments do not significantly affect the overall biodiversity impact score for companies operating in the north, while diseases do. Similar to the regression analysis for companies in the southwest and nationwide, the biodiversity variables lice counts and bottom conditions also show statistical significance for the companies operating in the north, however at a lower level. Our results indicates that companies operating in the northern production areas should mainly focus lice counts, bottom surveys and prevention of disease outbreaks to improve their overall biodiversity impact score when compared to other salmon farming companies operating in northern Norway.

| | Overall clustering score in northern production areas |
|---|---|
| Escapes | 0,161<br>(0,118) |
| Lice treatments | 0,117<br>(0,151) |
| Lice counts | $0,258^{**}$<br>(0,103) |
| Bottom surveys | $0,218^{*}$<br>(0,115) |
| Diseases | $0,251^{*}$<br>(0,126) |
| Slaughter weight 2020 | $-0,050^{**}$<br>(0,022) |
| Observations | 21 |
| $R^2$ | 0,705 |

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 16: Association between overall biodiversity clustering score in production areas 7-13 and the other biodiversity variables for the same areas. The standard deviation is shown within the parentheses. Slaughter weight in 1000 tonnes.

## 5.2 Listed salmon farming companies

The listed companies Mowi, Salmar, Lerøy and Grieg have in common that they are present both in the north and south and in more than one production area. Looking closer at their results in Table 13 and Table 14 combined, we see the best performer out of the companies is Mowi, which ranks first both among all northern operating companies and all southwestern operating companies in Norway. Concurrently, Grieg Seafood is ranked lowest among the "big four", ending up in the middle both in the northern and southern rankings.

In Figure 8, we see the historical scores on the different biodiversity impact variables for the large listed companies. A significant contributor to Mowi's excellent overall performance is its solid performance on bottom surveys. Performances on this parameter are likely to contribute to lower scores for Grieg during the last couple of years of the data set. Other observations worth mentioning includes Lerøy Seafood Group's consistently high disease levels. At the same time, they seem to be best-in-class on lice treatments. It should also be noted that Mowi is the worst performer among the listed players on lice levels for five out of six years in the data set. Finally, while the other listed companies blend out through notable performances in either direction, Salmar has a very consistent performance on all metrics - never really standing out in either direction.

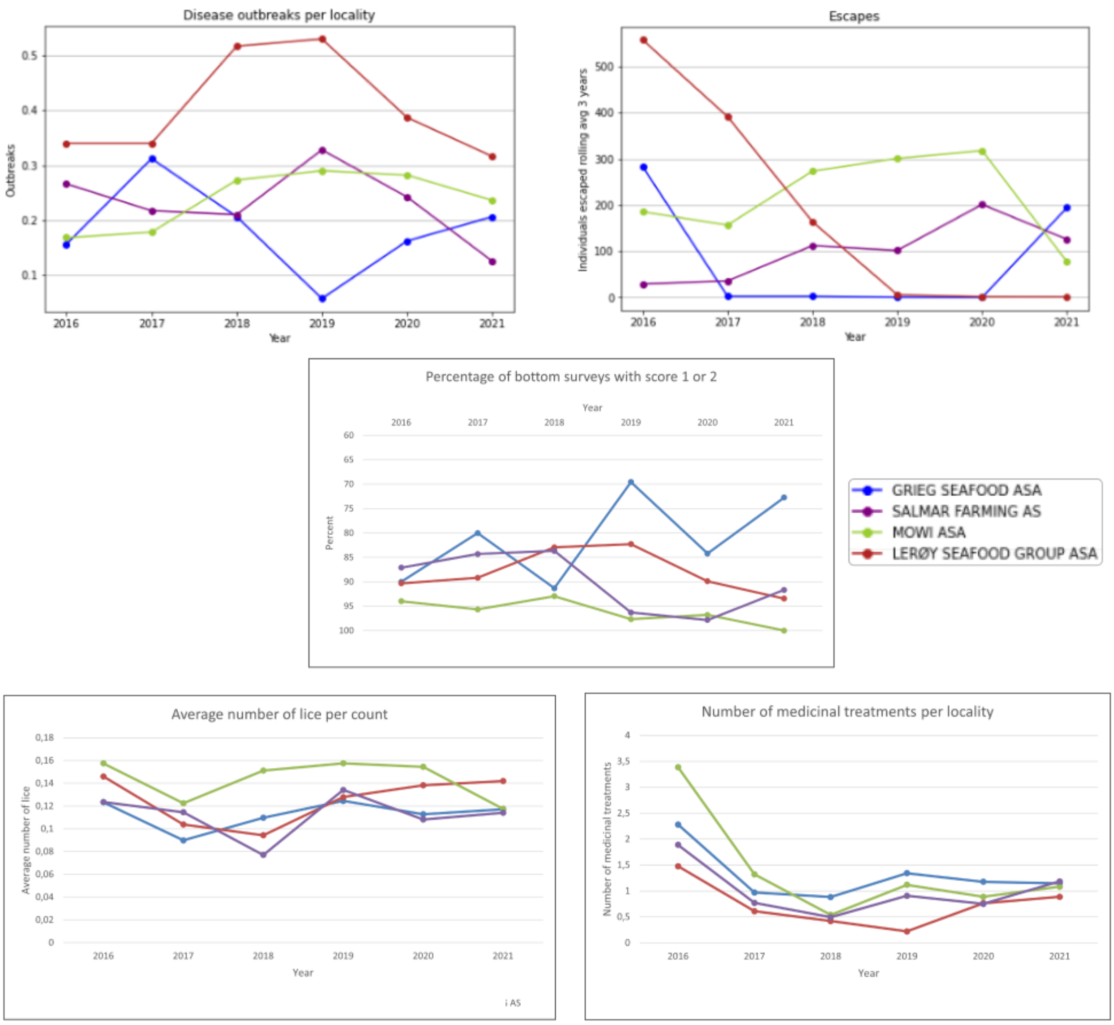


Figure 8: Performance on biodiversity parameters for the four fish farmers in our dataset listed on Oslo Stock Exchange. Note: the bottom survey diagram is inverted, so that lower (i.e., higher percentage for bottom surveys) is better in all diagrams.

## 5.3 Model robustness

To examine the robustness of our model, we perform additional analysis on the data in our data set with time series attributes. This extra analysis is needed since our clustering methodology is a novel assessment approach that considers both time series and non-time series data by aggregating them annually. Thus, we examine the robustness of our approach by applying both our methodology and a classical time series clustering to the biodiversity impact variables and then compare the results. We use dynamic time warping to cluster companies based on univariate time series, so that we can better capture the time series aspect of the relevant biodiversity impact variables; lice treatments, diseases and lice. These three variables can be put on a weekly format to facilitate time series analysis, as opposed to escapes and bottom surveys that have a different data structure unsuitable for time series analysis. Dynamic time warping is a technique to dynamically compare time series data when the time indices between comparison data points do not sync up perfectly (Zhang 2020). This algorithm is thus a suitable to deal with e.g. the data on lice counts. As lice levels are to a certain extent temperature-dependent, sea lice levels rise later in the year in the north of Norway than in the south and vice versa (Dalvin et al. 2019). With dynamic time warping, such effects can be mitigated, placing northern and southern operating salmon farming companies in the same clusters although their time series do not align perfectly.

The key question for the dynamic time warping model on time series is whether our cross-sectional clustering approach capture time series variance well enough. If it does, the time series-based model should be able to identify the same companies as good and bad performers that our K-means clustering approach on cross-sectional data described in Section 4. To answer this question, we divide the result tables from our K-means model on singular biodiversity impact variables nationwide into four quartiles. The 1st quartile contains the companies ranked as the top nine best performers. 4th quartile contains the companies ranked as the nine worst performers. If there is a tie for a ranking spot, cluster placements more recently are weighted more than cluster placements further back in time (e.g., placement in cluster 1 in 2019 outweighs placement in cluster 1 in 2017). For the time series clustering, we also use four clusters so that the number of clusters is aligned with the number used in the cross-sectional approach. Four clusters in the univariate time series clustering model is also sufficient to avoid outlier dominance and get at least two clusters containing more than nine companies, making a comparison between our two clustering approaches possible.

| **Variable** | **Correct classifications, 1st quartile** | **Correct classifications, 4th quartile** | **Total** |
|---|---|---|---|
| Diseases | $\frac{9}{9}$ | $\frac{9}{9}$ | $\frac{18}{18}$ |
| Sea lice | $\frac{8}{9}$ | $\frac{9}{9}$ | $\frac{17}{18}$ |
| Lice treatments | $\frac{8}{9}$ | $\frac{8}{9}$ | $\frac{16}{18}$ |
| Total | $\frac{25}{27}$ | $\frac{26}{27}$ | $\frac{51}{54}$ |

Table 17: The fraction of the best and worst nine performing companies from our cross-sectional clustering model which are ranked equal as through our dynamic time warping time series clustering model.

Table 17 shows that the dynamic time warping clustering model is able to capture much of the same trends as our main clustering model. The univariate time series clustering approach aligns well with our main clustering model, correctly placing $\frac{26}{27}$ companies in the 4th quartile of the ranking. It is also highly consistent in the 1st quartile, only missing out on two company placements.

For the lice counts, Tombregruppa is placed in the worst of two big clusters in the time series approach, while it is ranked within the top nine in the cross-sectional model. A misalignment between the two methods also occurs for the lice treatment variable in the dynamic time warping clustering model, where Hofseth Aqua is placed in a medium performing cluster out of three big clusters instead of the cluster with the best performers. The medium-performing cluster also contains Alsaker Fjordbruk, rated among the bottom nine on lice treatments in our main clustering model. Full cluster assignments of the dynamic time warping time series clustering algorithm can be found in Appendices N, O and P.

We conclude that our model based on the cross-sectional clustering approach in Section 4 sufficiently captures time series variance. Therefore, it can be relied on to provide robust results on biodiversity impact performances using time series-structured biodiversity impact variables.

# 6 Data quality

To be able to draw conclusions regarding the biodiversity impact of companies, it is vital to discuss issues related to data reliability. The regime of mandatory reports is enforced by different governmental institutions, each with its system and way of making the data publicly available. We therefore systematically describe our model's input sources and the methodological differences and uncertainties associated with them, and also assess the data quality for each input source.

Today, two central governmental institutions are responsible for monitoring environmental and biodiversity impacts of Norwegian aquaculture industry and the companies within it; the Directorate of Fisheries and the Norwegian Food Safety Authority. The Directorate of Fisheries handles the issues of escapes and bottom condition surveys, including keeping track of all aquaculture licenses in the Aquaculture Registry. The Norwegian Food Safety Authority (NFSA) is responsible for the issues of sea lice and medicinal usage in the industry. We interviewed employees from both organizations and investigated literature and best practices on the topic to gain insight into the data quality of the biodiversity impact variables we use in this thesis[11], in which our findings and insights is summarized in Table 18 below.

| Variable | Data quality | Comments |
|---|---|---|
| The Aquaculture Registry | High | Advantages:<br>- Updated frequently.<br>- Controlled and monitored by the Directorate of Fisheries.<br>Disadvantages:<br>- Difficult to identify which company that has the main<br>operational responsibility in joint-venture operated localities. |
| Lice counts | Medium | Advantages:<br>- Weekly reported data from all localities in Norway.<br>- Reported lice numbers rarely deviate from findings in NFSA-inspections.<br>- Strict sanctions if fish farmers are caught underreporting sea lice numbers.<br>Disadvantages:<br>- Only 10-20 out of 200 000 salmon per pen are counted during a licecount.<br>- Manually counted, quality depends on intuition and operator skills/experience. |
| Escapes | Low | Advantages:<br>- Authorities monitor escaped farmed salmon in the wild closely.<br>- Fish farmers have incentives to avoid escapes; one escapee is one less fish slaughtered.<br>Disadvantages:<br>- Fish farmers have relatively low control over the number of fish in their pens,<br>making it difficult to estimate the number of escaped salmon once an escape incident occurs.<br>- Incentives for fish farmers to underreport escape incidents. |
| Bottom condition surveys | Medium/high | Advantages:<br>- Accredited and independent third-party companies perform the surveys.<br>- Follow a strict methodological procedure described by a Norwegian Standard<br>document.<br>Disadvantages:<br>- Limited use on soft- and mixed bottoms.<br>- Only measures a limited area directly under the locality. |
| Lice treatments | High | Advantages:<br>- Reported medicinal use rarely deviate from findings in NFSA-inspections.<br>Disadvantages:<br>- Difficult to know how many pens that were treated if treatment only took place<br>for parts of the locality.<br>- Reported weekly while treatments last, and not on a per-treatment-basis. |
| Diseases | High | Advantages:<br>- Diseases are verified quickly by veterinarians from NFSA.<br>Disadvantages:<br>- Only a few diseases are required by law to report to the NFSA. |

Table 18: Summary of insights and findings from our data quality analysis on the biodiversity impact variables used in this thesis.

[11] We interviewed representatives both from the Norwegian Food Safety Authority and the Directorate of Fisheries. A Special Inspector from the Norwegian Food Safety Authority (February 6, 2022) and both a Senior Advisor and an Aquaculture Biologist from the Directorate of Fisheries (March 10, 2022).

### The Aquaculture Registry

The Aquaculture Registry is managed by the Directorate of Fisheries and is central to the regulation of aquaculture companies in Norway, as it contains an overview of aquaculture licenses, their legal holders and connected localities. It also contains the officially registered rights on these licenses. The registry was established in 2006 and is an assets register, with each license constituting a separate entity in the register. Updated in real-time, it is the primary source of information within the aquaculture industry in Norway. We assume the data quality of the Aquaculture Registry to be *high*.

### Sea lice

Reporting of sea lice numbers is regulated in the Regulations on the control of salmon lice in aquaculture facilities which came in place in 2013 (Ministry of Trade, Industry and Fisheries 2013a). The primary purpose of the regulation is to reduce the occurrence of salmon lice so that the harmful effects on fish in aquaculture facilities and wild stocks of salmonids are minimized. A secondary purpose is to reduce and combat the development of resistance among salmon lice against medicinal treatments used today. In order to comply with the regulation, fish farmers typically have to count sea lice at all their localities weekly. Fish farmers have to capture at least 10 representative salmon from every pen in the facility and count the number of sea lice on each individual while it is sedated. The regulation states that the number of mature female sea lice on every fish in the locality must be below 0,5 on average. The limit is stricter in periods when the wild salmon migrates through the Norwegian fjords, which is five weeks in the spring every year. These weeks, the threshold is lowered to 0,2. The regulation imposes that fish farmers who are unable to keep the sea lice numbers under these levels over time need to slaughter their stock of salmonids.

Regarding the quality of sea lice data, we have interviewed representatives from both the Norwegian Food Safety Authority and the Directorate of Fisheries. The Norwegian Food Safety Authority regularly carry out both announced and unannounced inspections at fish farming locations, and their representative stated that they rarely see any notable deviations from reported sea lice numbers. However, as there can be up to 200 000 individuals in a pen, and the sample size is 10-20 salmon, the result provides only a limited statistical representation of actual sea lice levels. Methods and technology to continuously count sea lice are being developed, aiming to track lice levels for every single fish in a pen. The Norwegian Food Safety Authority is encouraging more usage of automatic sea lice counting methods in the industry (Nedrejord 2022). Cermaq Norway AS is one of the companies which has been granted a dispensation to perform digital counting of lice using camera technology (Nygård 2021). It remains to see if automatic lice countings will become the industry standard. As of today, the majority of lice countings are still done manually and thus prone to error.

Manual lice counts are performed by the employees at the fish farms, using their own intuition and experience to separate and count the different lice types. Thus, one has to trust the employees that the reported sea lice data is correct in order to trust the data. One can argue that the fish farmers are incentivized to report lower sea lice numbers than counted, since measures and treatments to lower the sea lice numbers are costly. However, the Norwegian government has strict measures in place in case fish farmers temper with the sea lice numbers. In one case, the manager of a Norwegian fish farming company called Nord-Senja Laks AS was caught underreporting sea lice numbers for several weeks, keeping it hidden from The Norwegian Food Safety Authority (Sagmoen 2016). It was later revealed that the company had 15 times more female sea lice per salmon than allowed. The company manager was sentenced to 6 months in prison, and the company had to pay 5 million NOK in fines. Several aggravating circumstances were highlighted in the conviction, most notably that Nord-Senja Laks AS undermined the trust given to the industry by the authorities in the form of acceptance of self-reported lice numbers. This verdict was meant to be a deterrent so other fish farmers would not risk cheating with their sea lice numbers in the future.

Sea lice data from Norwegian fish farmers seem to be trustworthy since the government is regulating it very strictly, and fish farmers risk considerable penalties being caught tempering the reported sea lice numbers. Factors that make the data less trustworthy are manually reporting of data, counting based on intuition/experience, company incentives to report lower numbers and that only 20 out of approximately 200 000 fish are being counted in each pen. However, as (un)announced inspections by The Norwegian Food Safety Authority rarely reveal deviations from reported numbers, we classify the data quality of lice numbers as *medium*.

#### Escapes

The reporting and handling of escape incidents is regulated in the Aquaculture Operations Regulations, which is a part of The Aquaculture Act (Ministry of Trade, Industry and Fisheries 2021a). The regulations state clearly that all fish farmers have a duty to prevent and limit escapes of farmed salmon. This includes a whole range of preventive escape measures. The regulation also covers fish farmers' duty to report escapes incidents and implement measures of recapture. It is the Directorate of Fisheries that has the responsibility to handle escape incidents, as fish farmers report directly to them whenever escapes occur.

After interviewing representatives from the Directorate of Fisheries, we got the impression that the quality of escape data is poor. They stated that salmon farming companies lack control of the number of salmon in their pens for various reasons, the main one being the large number of salmon per pen and the high mortality rates. Today, there are no precise methods to estimate the number of escaped individuals whenever an escape incident has occurred (Hytterød 2021). According to the Directorate of Fisheries' representatives, there have been cases where fish farmers enumerate more fish in their pens after an escape event than they initially thought they had before the incident. In addition, fish farmers also have incentives to report lower escape numbers than actual due to possible prosecution and loss of reputation. This is a challenging balancing act for the reporting regime, as companies that report all their escape events risk being punished, while those that avoid reporting don't - and there is no credible way to verify whether the reports are done truthfully (Njåstad 2021). There is reason to believe that some escape incidents never get reported, as fishermen fishing for wild fish have occasionally reported catching farmed salmon in their nets in an area where there were no reported escape events of farmed salmon (Hytterød 2021).

To improve these data quality issues, new technology and methods should be developed. The first necessary step is that fish farmers get better control of the number of individuals and more accurate estimates of the total biomass in their pens. Machine learning and new camera systems could help fish farmers with this, as most of the counting of fish and individual controls are done manually today. As of today, no system has the capability of counting the exact numbers of fish in a pen. Until a data-driven and automatic solution shows proof of concept, we assume the data quality of escapes to be *low*, due to several unreported incidents and rather significant uncertainties regarding the numbers of escaped farmed salmon.

#### Bottom condition surveys

Fish farmers have to monitor their environmental impacts according to regulations in the Aquaculture Operations Regulations. An inspection of the bottom conditions under the fish farming locations has to be done according to the Norwegian Standard document "NS-9410", which describes a method for measuring and monitoring bottom conditions in fish farms (Standard Norge 2016). The regulation states that the surveys must be done by an independent third party that can document relevant professional competence. According to the regulations, the bottom surveys shall be carried out at the time of the production cycle when the environmental load or biomass is at its maximum. The bottom survey scores range from 1 to 4, where 1 is defined as "very good" and 4 is "very bad" in terms of environmental bottom condition impacts under the location. Suppose a location gets a score of 4 on the bottom condition survey. In that case, the company has to implement measures to reduce its impact on the environment under their location and also do bottom surveys more frequently. If the measures do not improve the bottom conditions, the government can demand that a company abandon the locality for some time to let the bottom environment recover.

Since the third-party companies get paid by the fish farming companies to do the bottom condition surveys, this might influence the independence of the reported scores. However, the third-party companies perform the bottom surveys under a regime of several quality control layers. First of all, there are clear reporting guidelines. Secondly, Norwegian Accreditation has yearly supervision of the third party consultancy companies to ensure they have the competency, independence and integrity needed to do the bottom surveys. The third quality layer is the Directorate of Fisheries, which does quality checks of the surveys and follows up on the accreditation of the third-party companies. Another issue that can potentially lead to lower data quality could be errors in how the surveys are being done. For example, today's method is meant for soft bottom samples, and it gives limited value if used under a location with a hard or mixed bottom. The Directorate of Fisheries representative we talked to said that the samples might look very good for these surveys, but it may not be the case in reality.

Whether a locality gets a good score or not depends a lot on current conditions and how the company chooses to utilize its given maximum production capacity. However, the most critical factor is the specific company's operation, or in other words, how they implement measures to reduce their environmental bottom impacts. One such factor is feeding, as continuously overfeeding will have a negative impact since it is an organic material and impacts life on the seabed. Empirically, the Directorate of Fisheries notices large deviations from company to company regarding how aware and concerned they are about their environmental bottom impacts. They generally see that when a company performs poorly at one environmental factor, they are also performing poorly at other environmental and biodiversity impact factors.

As bottom surveys are conducted in a standardized way by a certified supplier under a strict quality regime and within given intervals, the results provided from these surveys seem trustworthy. However, as these surveys are not as applicable to localities over mixed or hard bottom, we assume the data quality to be *medium/high*.

#### Lice treatments

Treatment of sea lice is regulated in "Regulations on the control of salmon lice in aquaculture facilities" (Ministry of Trade, Industry and Fisheries 2013a), which also describes how companies need to report every lice treatment they perform. In addition to this, it is mandatory to report the amount and type of active substance used, sea temperature, sensitivity analysis results and if there is any suspicion of resistance against the substance used. The Norwegian Food Safety Authority is the responsible authority, keeping track of Norwegian fish farmers' lice treatments and medicinal usage.

A Norwegian Food Safety Authority representative stated in an interview with us that they rarely see any deviations from reported medicinal usage when they check samples of salmon during their announced and unannounced inspections on localities. It can be argued that salmon farming companies have incentives to use as few treatments as possible, as sea lice treatments are expensive and are related to increased mortality rates (Sviland Walde et al. 2021). One challenge with the lice treatment data is that it is reported every week, which means that one single treatment lasting over several weeks gets registered as more than one lice treatment. The data also only separate between treatments of the "whole location" or only "parts of the location", which in some cases could be only one out of many pens. In the bigger context, these challenges seem to be minor. Therefore, we assess the quality of lice treatment data to be *high*.

#### Diseases

Diseases among farmed salmon are reported to and handled by the Norwegian Food Safety Authority, and regulated by the "Regulations on the prevention and control of infectious diseases in aquatic animals" (Ministry of Trade, Industry and Fisheries 2008). The regulations state that in the event of increased mortality, except when the mortality is obviously not caused by illness, a health check must be carried out without undue delay to clarify the cause. A veterinarian or fish health biologist must carry out the health check.

To diagnose the diseases ISA or PD, personnel from the Norwegian Food Safety Authority perform an autopsy of the fish suspected to have the disease. The Norwegian Veterinary Institute receives samples of tissues from different organs, together with an overview of the medical history of the fish currently in the water. Further, the samples are examined using different techniques, as it is demanded that virus presence must be confirmed by two different methods to declare a disease outbreak. All the salmon in a locality with ISA-diagnosis is considered infected, and usually the Norwegian Food Safety Authority will demand the infected salmon slaughtered as fast as possible. On the other side, if a PD-outbreak is confirmed, it is only recommended to slaughter the whole location (Ministry of Trade, Industry and Fisheries 2008).

As licensed professionals confirm disease outbreaks, the only issue with data quality is companies failing to implement adequate health control. This happens when a locality experiences substantially increased mortality rates without anyone taking action. As this would most likely be discovered in a later step of the value chain, and Norwegian authorities prosecute the responsible ones (Olsen 2019), such events are assumed to be rare and thus have a low effect on overall data quality. Therefore, we assess the data quality for the disease variable to be *high*.

# 7 Conclusion

The investment world has seen an increased interest in ESG factors over the latest decades, and more focus and attention is being pointed towards biodiversity impacts from financial institutions, authorities and companies due to several emerging trends. This also applies to Norway's second-largest export industry; aquaculture. Existing literature on biodiversity impacts from the Norwegian aquaculture industry focus primarily on single biodiversity impact variables at a time, and at an industry level instead of a company level. Our contribution to the literature is a biodiversity impact assessment and investigation on the company level, where we look into several biodiversity impact variables simultaneously for Norwegian aquaculture companies over a longer period of time. We utilize publicly available data over the last six years on lice counts, escapes, diseases and lice treatments in order to rank the Norwegian salmon farming companies biodiversity impact performance. Our methodology provide a tool to assess which companies performing best and worst on biodiversity impact in the Norwegian aquaculture industry, focusing on the growth phase where the salmon is kept in open pens in the sea by using relevant and effective biodiversity impact indicators specific for the aquaculture industry.

To develop a ranking methodology treating all salmon farming companies fairly, we first combine five data sources into an extensive data set. Altogether, our final data set covers the 36 largest salmon farming companies in terms of slaughter weight covering the period 2016 to 2021. For all five biodiversity impact variables and all companies, we measure our variables on a yearly basis. We apply a K-means clustering algorithm to classify and categorize similar performing companies into four distinct clusters. These clusters are identified from "Top biodiversity impact performers" to "Low biodiversity impact performers". Finally, all companies are ranked overall, from best performing to worst performing, by aggregating their cluster placements from 2016 to 2021.

First, when comparing the companies nationwide, we find that the best performing companies in the ranking are mainly salmon farming companies with localities exclusively in the northern production areas of Norway. Concurrently, the poorest performing companies on the nationwide biodiversity impact ranking primarily consist of companies operating in the southwestern production areas of Norway. The geographically diversified salmon farming companies with localities both in the northern and southwestern production areas are dragged down by their performances in the south and up by their northern performances, ending up with medium performances in the middle on the nationwide biodiversity impact ranking. Secondly, we investigate which biodiversity impacts variables that influence the overall rating most by applying an ordinary least square regression analysis, finding that it is mainly influenced by performances on the variables sea lice, diseases and bottom conditions. In the nationwide comparison, we find that performance on escapes and lice treatments does not significantly contribute to the ranking of companies.

Third, since our results on a nationwide basis indicate a strong correlation between biodiversity impact performance score and geographic location of the companies localities in Norway, we split the data set into a southern part and a northern part. We rank the companies using our biodiversity impact clustering methodology separately for production areas 1-6 (southwestern Norway) and 7-13 (northern Norway). Our results show that the big listed companies is ranking high on biodiversity impact performance in both parts of the country. In the southern production areas, the five best-performing companies out of 20 are all publicly traded. For the companies operating in the northern areas of Norway, all the listed salmon farming companies are placed among the top half of the 21 northern companies. Mowi, the world‘s largest salmon farming company, is ranked 1st in both the southwestern and the northern ranking of biodiversity impact performance. Cermaq Norway, Wilsgård Fiskeoppdrett and Nova Sea, three of the best performing companies in the nationwide analysis, also get placed among the best performers when compared to other companies operating in the northern production areas in Norway. However, for the companies Gildeskål Forskningsstasjon and Kleiva Fiskefarm, the opposite effect is observed when splitting the data set between southwestern and northern Norway. One reason is that the five biodiversity impact variables are weighted differently when only companies in northern production areas are considered. Another reason is that the performance of all comparable companies, especially on lice and diseases, is increased when only comparing biodiversity impact performance among companies operating in the north.

Lastly, to ensure model robustness, we look into the biodiversity impact variables in our data set most suitable for time series analysis; lice counts, diseases and delousing treatments. We then perform univariate time series clustering through dynamic time warping, investigating if the time series model is able to label the same companies as good and bad performers for singular biodiversity impact variables as our K-means clustering methodology. The dynamic time warping model places the best and worst-performing companies in the "correct" clusters with an accuracy of 94% on average out of the three biodiversity impact variables, indicating that our K-means clustering methodology is robust. Moreover, we provide an extensive review and discussion on the data quality of our selected biodiversity impact variables. Key insights from this review is that the data quality on escapes is poor, mainly due to uncertain numbers of salmon in the pens before the escapes incidents happen. For the other variables, the data quality ranges from medium (lice counts) via medium/high (bottom condition surveys) to high (lice treatments and diseases). However, considering the poor quality on escape data, our results are robust as escapes show the least influence on the overall clustering in our regression analysis.

We have identified several interesting topics for further research that could complement our findings. First, future studies could employ more relevant biodiversity impact variables such as mortality data, feed-conversion ratios and share of localities that are certified.[12] However, there are certain limitations regarding data quality and accessibility concerning mortality data and feed-conversion ratios. It would also be interesting for further studies to exclude the escape variable and see how the results change, as this is the variable in our analysis with the lowest data quality and biggest uncertainties. Second, additional data sources could be employed by future studies to cover more of the impacts from the salmon farming companies' value chain by investigating biodiversity impacts from activities such as smolt production, feed usage, slaughtering and transport of the salmonids. Third, further research could include companies on a global scale and thus compare and measure biodiversity impact internationally. Moreover, it would be interesting for further research to see if biodiversity impact analysis could be used to predict future biodiversity impact performance of companies, which would be helpful for financial institutions and portfolio managers to make investment decisions. Lastly, further studies can investigate the relation between biodiversity impact performance and financial performance, analyzing whether companies performing well on biodiversity impact also performs well financially or are valued higher in the financial markets.

[12] Environmental certifications such as Global G.A.P, Aquaculture Stewardship Council (ASC) and Best Aquaculture Practices (BAP) is given to fish farming companies if they fulfill a certain number of demands regarding sustainability.

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# Appendix

## A Descriptive data for final data sets

| Year | Min | Max | Mean | SD | 25th Q | Median | 75th Q | Skewness | Kurtosis | Number of observations |
|---|---|---|---|---|---|---|---|---|---|---|
| 2021 | 0 | 1946,117 | 110,258 | 340,037 | 0,000 | 0,828 | 37,220 | 4,507 | 24,238 | 36 |
| 2020 | 0 | 1946,117 | 107,636 | 330,711 | 0,000 | 2,470 | 60,032 | 4,826 | 27,464 | 53 |
| 2019 | 0 | 1946,117 | 104,642 | 324,295 | 0,010 | 3,940 | 62,412 | 5,093 | 30,089 | 49 |
| 2018 | 0 | 1165,180 | 109,717 | 224,441 | 0,000 | 1,557 | 119,570 | 3,224 | 13,317 | 37 |
| 2017 | 0 | 2552,177 | 196,455 | 473,565 | 0,000 | 1,322 | 139,427 | 3,710 | 17,079 | 36 |
| 2016 | 0 | 2631,287 | 287,249 | 606,974 | 0,000 | 14,525 | 257,337 | 2,868 | 8,997 | 32 |
| | | | | | | | | | Total | 243 |

Table 19: Descriptive statistics before normalizing for escaped farmed salmon variable: rolling average of number of escapees per locality over a three year period. Sample: 36 companies.

| Year | Min | Max | Mean | SD | 25th Q | Median | 75th Q | Skewness | Kurtosis | Number of observations |
|---|---|---|---|---|---|---|---|---|---|---|
| 2021 | 0,044 | 0,206 | 0,124 | 0,045 | 0,100 | 0,121 | 0,156 | -0,082 | -0,806 | 45 229 |
| 2020 | 0,038 | 0,259 | 0,131 | 0,052 | 0,097 | 0,123 | 0,158 | 0,694 | 0,097 | 44 353 |
| 2019 | 0,040 | 0,247 | 0,138 | 0,055 | 0,090 | 0,130 | 0,183 | 0,305 | -0,809 | 43 623 |
| 2018 | 0,043 | 0,275 | 0,126 | 0,057 | 0,086 | 0,104 | 0,164 | 0,965 | 0,206 | 43 673 |
| 2017 | 0,048 | 0,728 | 0,139 | 0,107 | 0,099 | 0,122 | 0,140 | 0,730 | 0,531 | 44 533 |
| 2016 | 0,038 | 0,319 | 0,138 | 0,055 | 0,111 | 0,127 | 0,161 | 0,739 | 2,182 | 44 127 |
| | | | | | | | | | Total | 265 538 |

Table 20: Descriptive statistics before normalizing for lice counts variable: average number of lice per salmon over the whole year. Sample: 36 companies.

| Year | Min | Max | Mean | SD | 25th Q | Median | 75th Q | Skewness | Kurtosis | Number of observations |
|---|---|---|---|---|---|---|---|---|---|---|
| 2021 | 0 | 0,818 | 0,229 | 0,188 | 0,100 | 0,200 | 0,304 | 1,248 | 1,782 | 178 |
| 2020 | 0 | 1,200 | 0,246 | 0,247 | 0,049 | 0,170 | 0,398 | 1,691 | 4,807 | 197 |
| 2019 | 0 | 0,833 | 0,254 | 0,248 | 0,000 | 0,200 | 0,527 | 0,540 | -1,003 | 223 |
| 2018 | 0 | 0,920 | 0,268 | 0,256 | 0,000 | 0,221 | 0,440 | 0,696 | -0,279 | 235 |
| 2017 | 0 | 0,867 | 0,298 | 0,262 | 0,000 | 0,293 | 0,497 | 0,400 | -0,983 | 216 |
| 2016 | 0 | 1,000 | 0,256 | 0,267 | 0,000 | 0,153 | 0,388 | 1,071 | 0,601 | 201 |
| | | | | | | | | | Total | 1 250 |

Table 21: Descriptive statistics before normalizing for disease case variable: number of disease outbreaks per locality per year. Sample: 36 companies.

| Year | Min | Max | Mean | SD | 25th Q | Median | 75th Q | Skewness | Kurtosis | Number of observations |
|---|---|---|---|---|---|---|---|---|---|---|
| 2021 | 54,545 | 100 | 87,786 | 13,674 | 77,679 | 92,262 | 100,000 | -0,994 | 0,250 | 547 |
| 2020 | 42,857 | 100 | 86,705 | 11,200 | 80,000 | 87,500 | 96,992 | -0,982 | 1,941 | 624 |
| 2019 | 61,538 | 100 | 86,116 | 11,280 | 77,778 | 86,607 | 98,235 | -0,291 | -0,909 | 578 |
| 2018 | 61,538 | 100 | 87,706 | 12,536 | 77,083 | 90,097 | 100,000 | -0,542 | -1,084 | 546 |
| 2017 | 40,000 | 100 | 87,143 | 12,841 | 80,000 | 88,889 | 100,000 | -1,387 | 3,422 | 501 |
| 2016 | 54,545 | 100 | 92,694 | 10,864 | 86,989 | 100,000 | 100,000 | -1,779 | 3,521 | 492 |
| | | | | | | | | | Total | 3 288 |

Table 22: Descriptive statistics before normalizing for bottom condition metric: percentage of surveys that were either score 1 or 2. Sample: 36 companies.

| Year | Min | Max | Mean | SD | 25th Q | Median | 75th Q | Skewness | Kurtosis | Number of observations |
|---|---|---|---|---|---|---|---|---|---|---|
| 2021 | 0,000 | 7,429 | 1,246 | 1,198 | 0,720 | 1,070 | 1,361 | 3,797 | 19,708 | 3511 |
| 2020 | 0,059 | 6,857 | 1,391 | 1,250 | 0,619 | 1,070 | 0,059 | 2,358 | 8,951 | 3456 |
| 2019 | 0,053 | 5,750 | 1,360 | 1,124 | 0,650 | 1,038 | 0,053 | 1,822 | 5,091 | 2952 |
| 2018 | 0,000 | 3,273 | 1,060 | 0,777 | 0,490 | 1,022 | 1,390 | 0,970 | 1,060 | 2318 |
| 2017 | 0,000 | 6,667 | 1,756 | 1,624 | 0,653 | 1,281 | 1,917 | 1,398 | 1,405 | 2478 |
| 2016 | 0,400 | 16,240 | 3,368 | 3,020 | 1,754 | 2,574 | 3,500 | 2,711 | 9,430 | 3257 |
| | | | | | | | | | Total | 17972 |

Table 23: Descriptive statistics before normalizing for lice treatments variable: number of medicinal treatments per locality per year. Sample: 36 companies.

## B Number of localities per company 2016-2021

| Company | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 |
|---|---|---|---|---|---|---|
| Alsaker Fjordbruk AS | 27 | 27 | 25 | 23.5 | 23.5 | 22.5 |
| Bjørøya AS | 6.0 | 6.0 | 10.5 | 10.5 | 9.0 | 10.0 |
| Blom Fiskeoppdrett AS | 10.5 | 10.5 | 10.5 | 11.5 | 11.0 | 13.0 |
| Bolaks AS | 11.0 | 11.0 | 10.0 | 11.5 | 13.5 | 13.5 |
| Bremnes Seashore AS | 26.5 | 26.5 | 24.5 | 22.0 | 20.0 | 21.5 |
| Cermaq Norway AS | 45.0 | 45.0 | 45.0 | 44.5 | 44.5 | 45.5 |
| Egil Kristoffersen & Sønner AS | 8 | 8 | 8 | 9 | 9 | 8.5 |
| Eide Fjordbruk AS | 7.5 | 7.5 | 8.0 | 6.5 | 5.5 | 6.0 |
| Eidsfjord Sjøfarm AS | 20.0 | 20.0 | 19.5 | 19.0 | 16.0 | 17.0 |
| Ellingsen Seafood AS | 15 | 15 | 13.0 | 10.0 | 11.0 | 11.0 |
| Emilsen Fisk AS | 5.0 | 5.0 | 4.5 | 5.0 | 8.0 | 9.5 |
| Erko Seafood AS | 12.5 | 12.5 | 12.5 | 13 | 13.0 | 10.0 |
| Firda Sjøfarmer AS | 17 | 17 | 17 | 17 | 17 | 16.5 |
| Flakstadvåg Laks AS | 6 | 6 | 7 | 7 | 7 | 7 |
| Gildeskål Forskningsstasjon AS | 4.0 | 4.0 | 4.0 | 4.0 | 4.0 | 4.0 |
| Grieg Seafood ASA | 32.0 | 32.0 | 34.0 | 35.0 | 34.0 | 34.0 |
| Hofseth Aqua AS | 6 | 6 | 6 | 6 | 6 | 5.5 |
| Kleiva Fiskefarm AS | 4.5 | 4.5 | 4.5 | 5.0 | 5.0 | 5.0 |
| Kobbevik og Furuholmen Oppdrett AS | 5.0 | 5.0 | 5.0 | 5.0 | 5.0 | 5.5 |
| Lerøy Seafood Group ASA | 101.5 | 101.5 | 102.5 | 100.0 | 97.0 | 98.0 |
| Lingalaks AS | 10.5 | 10.5 | 9.0 | 9.5 | 9.5 | 12.0 |
| Lovundlaks AS | 6 | 6 | 5 | 6.5 | 5.0 | 6.5 |
| Mowi ASA | 152.0 | 152.0 | 146.5 | 139.5 | 140.0 | 144.0 |
| Måsøval AS | 12.5 | 12.5 | 12.0 | 15.0 | 16.0 | 17.5 |
| Nordlaks Oppdrett AS | 36.5 | 36.5 | 35.5 | 33.0 | 34.0 | 35.0 |
| Nova Sea AS | 27.5 | 27.5 | 26.5 | 19.5 | 19.5 | 20.0 |
| NRS Farming AS | 30.0 | 30.0 | 33.5 | 32.5 | 26.5 | 26.5 |
| Osland Havbruk AS | 6 | 6 | 5.5 | 4.0 | 3.5 | 3.5 |
| Salaks AS | 6 | 6 | 8 | 8 | 8 | 8 |
| Salmar Farming AS | 71.5 | 71.5 | 69.0 | 64.0 | 64.0 | 60.0 |
| Salmonor AS | 19.5 | 19.5 | 19.0 | 19.0 | 20.5 | 20.5 |
| SinkabergHansen AS | 12.0 | 12.0 | 11.0 | 8.5 | 10.0 | 11.0 |
| Steinvik Fiskefarm AS | 7.0 | 7.0 | 7.0 | 7.0 | 8.0 | 8.0 |
| Sulefisk AS | 5 | 5 | 5.5 | 6 | 6 | 7.5 |
| Tombregruppa | 9 | 9 | 9 | 7.5 | 8.0 | 7.5 |
| Wilsgård Fiskeoppdrett AS | 3.0 | 3.0 | 3.5 | 3.5 | 3.5 | 3.5 |

Table 24: How many localities each fish farmer is operating alone or as an equal partner as of January 1st the given year. A locality operated only by one company is weighted 1, while a locality operated by partners is weighted at 0,5 each. As numbers for 2016 were inaccessible, we use 2017-numbers as a proxy for the 2016 number of localities. (Kystverket 2022).

## C Production areas


Figure 9: Overview of production zones along the Norwegian coastline. When making designated comparisons for operations in the north and the south, we split between production areas 6 and 7. Source: Barents Watch (2022)

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# D Locality structure for companies in our data set

| Company | Production zone | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** | **12** | **13** | Total | Percentage of total |
| Alsaker Fjordbruk AS | 0 | 7 | 15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 2,5 % |
| Bolaks AS | 0 | 0 | 21 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 2,4 % |
| Bjørøya AS | 0 | 0 | 0 | 0 | 0 | 4 | 17 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 2,4 % |
| Blom Fiskeoppdrett AS | 0 | 0 | 0 | 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 12 | 1,3 % |
| Bremnes Seashore AS | 0 | 8 | 18 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 26 | 2,9 % |
| Cermaq Norway AS | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20 | 0 | 0 | 28 | 0 | 48 | 5,4 % |
| Egil Kristoffersen og Sønner AS | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10 | 0 | 0 | 0 | 0 | 10 | 1,1 % |
| Eide Fjordbruk AS | 0 | 0 | 4 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10 | 1,1 % |
| Eidsfjord Sjøfarm AS | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10 | 3 | 3 | 0 | 0 | 16 | 1,8 % |
| Ellingsen Seafood AS | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10 | 0 | 0 | 0 | 0 | 10 | 1,1 % |
| Emilsen Fisk AS | 0 | 0 | 0 | 0 | 0 | 0 | 15 | 0 | 0 | 0 | 0 | 0 | 0 | 15 | 1,7 % |
| Erko Seafood AS | 0 | 0 | 4 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 11 | 1,2 % |
| Firda Sjøfarmer AS | 0 | 0 | 0 | 17 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 17 | 1,9 % |
| Flakstadvåg Laks AS | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 8 | 0 | 0 | 0 | 8 | 0,9 % |
| Gildeskål Forskningsstasjon AS | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 1 | 0 | 0 | 0 | 0 | 8 | 0,9 % |
| Grieg Seafood ASA | 0 | 16 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 0 | 38 | 4,3 % |
| Hofseth Aqua AS | 0 | 0 | 0 | 0 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 6 | 0,7 % |
| Kleiva Fiskefarm AS | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 11 | 0 | 0 | 0 | 11 | 1,2 % |
| Kobbevik og Furuholmen Oppdrett AS | 0 | 0 | 0 | 6 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 0,8 % |
| Lerøy Seafood Group ASA | 0 | 0 | 37 | 14 | 2 | 34 | 0 | 0 | 0 | 21 | 0 | 0 | 7 | 115 | 12,9 % |
| Lingalaks AS | 0 | 0 | 9 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 12 | 1,3 % |
| Lovundlaks AS | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 9 | 0 | 0 | 0 | 0 | 0 | 9 | 1,0 % |
| Mowi ASA | 5 | 14 | 15 | 17 | 15 | 29 | 17 | 19 | 9 | 0 | 7 | 0 | 0 | 147 | 16,5 % |
| Måsøval AS | 0 | 0 | 0 | 0 | 1 | 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 13 | 1,5 % |
| Nordlaks Oppdrett AS | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 15 | 0 | 0 | 0 | 37 | 4,2 % |
| Nova Sea AS | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 26 | 0 | 0 | 0 | 0 | 0 | 26 | 2,9 % |
| NRS Farming AS | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 2 | 16 | 0 | 25 | 2,8 % |
| Osland Havbruk AS | 0 | 0 | 0 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 0,8 % |
| Salaks AS | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 9 | 0 | 0 | 0 | 9 | 1,0 % |
| Salmar ASA | 0 | 0 | 0 | 0 | 13 | 35 | 6 | 0 | 0 | 10 | 5 | 6 | 8 | 83 | 9,3 % |
| Salmonor AS | 0 | 0 | 0 | 0 | 0 | 0 | 27 | 0 | 0 | 0 | 0 | 0 | 0 | 27 | 3,0 % |
| Sinkaberghansen AS | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 8 | 0 | 0 | 0 | 0 | 0 | 29 | 3,3 % |
| Steinvik Fiskefarm AS | 0 | 0 | 0 | 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 9 | 1,0 % |
| Sulefisk AS | 0 | 0 | 0 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 6 | 0,7 % |
| Tombregruppa | 0 | 0 | 6 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 11 | 1,2 % |
| Wilsgård Fiskeoppdrett AS | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 | 2 | 0 | 0 | 9 | 1,0 % |
| Total | 5 | 45 | 129 | 109 | 38 | 114 | 103 | 69 | 82 | 91 | 19 | 72 | 15 | 891 | 100% |
| Percentage of total | 0,6 % | 5,1 % | 14,5 % | 12,2 % | 4,3 % | 12,8 % | 11,6 % | 7,7 % | 9,2 % | 10,2 % | 2,1 % | 8,1 % | 1,7 % | 100% | |

Table 25: Locality structure of the companies (including joint-venture localities) in our final data set as of end of 2021. Source: BarentsWatch (2022)

## E Overall nationwide ranking

| Rank | Index | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | Total |
|---|---|---|---|---|---|---|---|---|
| *1* | Cermaq Norway AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Gildeskål Forskningsstasjon | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Kleiva Fiskefarm AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Nova Sea AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Wilsgård Fiskeoppdrett AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *6* | Bjørøya AS | 1 | 2 | 1 | 1 | 1 | 1 | 7 |
| *6* | Salmonor AS | 1 | 2 | 1 | 1 | 1 | 1 | 7 |
| *8* | Flakstadvåg Laks AS | 1 | 1 | 1 | 2 | 1 | 1 | 7 |
| *9* | Mowi ASA | 1 | 1 | 1 | 3 | 1 | 1 | 8 |
| *10* | Ellingsen Seafood AS | 1 | 1 | 1 | 1 | 2 | 2 | 8 |
| *11* | Lovundlaks AS | 1 | 1 | 1 | 1 | 1 | 3 | 8 |
| *12* | Emilsen Fisk AS | 2 | 2 | 2 | 1 | 1 | 1 | 9 |
| *13* | SinkabergHansen AS | 1 | 2 | 2 | 1 | 2 | 1 | 9 |
| *14* | Salaks AS | 1 | 1 | 2 | 2 | 1 | 2 | 9 |
| *15* | Grieg Seafood ASA | 1 | 2 | 1 | 1 | 1 | 3 | 9 |
| *16* | Eidsfjord Sjøfarm AS | 1 | 1 | 2 | 1 | 1 | 3 | 9 |
| *17* | NRS Farming AS | 2 | 1 | 2 | 1 | 1 | 3 | 10 |
| *18* | Nordlaks Oppdrett AS | 2 | 1 | 1 | 2 | 1 | 3 | 10 |
| *19* | Salmar Farming AS | 2 | 2 | 2 | 3 | 1 | 1 | 11 |
| *20* | Lerøy Seafood Group ASA | 2 | 2 | 2 | 4 | 1 | 2 | 13 |
| *21* | Tombregruppa | 3 | 2 | 2 | 1 | 2 | 3 | 13 |
| *22* | Bolaks AS | 3 | 2 | 2 | 3 | 2 | 2 | 14 |
| *23* | Måsøval AS | 1 | 2 | 3 | 3 | 3 | 2 | 14 |
| *24* | Egil Kristoffersen & Sønner | 1 | 3 | 2 | 2 | 3 | 3 | 14 |
| *25* | Kobbevik Og Furuholmen | 1 | 2 | 3 | 3 | 4 | 2 | 15 |
| *26* | Lingalaks AS | 2 | 2 | 2 | 4 | 2 | 3 | 15 |
| *27* | Steinvik Fiskefarm AS | 1 | 3 | 4 | 4 | 2 | 2 | 16 |
| *28* | Hofseth Aqua AS | 3 | 2 | 3 | 3 | 3 | 2 | 16 |
| *29* | Alsaker Fjordbruk AS | 2 | 2 | 3 | 4 | 3 | 2 | 16 |
| *30* | Osland Havbruk AS | 1 | 3 | 1 | 3 | 4 | 4 | 16 |
| *31* | Erko Seafood AS | 3 | 3 | 3 | 3 | 3 | 2 | 17 |
| *32* | Bremnes Seashore AS | 3 | 3 | 3 | 4 | 3 | 2 | 18 |
| *33* | Firda Sjøfarmer AS | 4 | 3 | 3 | 2 | 3 | 3 | 18 |
| *34* | Sulefisk AS | 3 | 3 | 4 | 2 | 3 | 4 | 19 |
| *35* | Blom Fiskeoppdrett AS | 2 | 3 | 3 | 4 | 3 | 4 | 19 |
| *36* | Eide Fjordbruk AS | 4 | 4 | 1 | 4 | 4 | 3 | 20 |

Table 26: Overall rating with yearly cluster placements. Input data is all five biodiversity factors annually from 2016-2021.

## F Escape nationwide ranking

| Rank | Index | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | Total |
|---|---|---|---|---|---|---|---|---|
| *1* | Egil Kristoffersen & Sønner | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Ellingsen Seafood AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Erko Seafood AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Flakstadvåg Laks AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Gildeskål Forskningsstasjon As | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Kleiva Fiskefarm As | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Kobbevik Og Furuholmen Oppdrett | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Måsøval AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | NRS Farming AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Osland Havbruk AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Salaks AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Steinvik Fiskefarm AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Sulefisk AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *14* | Alsaker Fjordbruk AS | 2 | 1 | 1 | 1 | 1 | 1 | 7 |
| *15* | Cermaq Norway AS | 1 | 1 | 1 | 2 | 1 | 1 | 7 |
| *15* | Emilsen Fisk AS | 1 | 1 | 1 | 2 | 1 | 1 | 7 |
| *15* | Nordlaks Oppdrett AS | 1 | 1 | 1 | 2 | 1 | 1 | 7 |
| *18* | Eidsfjord Sjøfarm AS | 2 | 2 | 1 | 1 | 1 | 1 | 8 |
| *19* | Nova Sea AS | 2 | 1 | 2 | 1 | 1 | 1 | 8 |
| *20* | Bremnes Seashore AS | 1 | 1 | 2 | 2 | 1 | 1 | 8 |
| *20* | Hofseth Aqua AS | 1 | 1 | 2 | 2 | 1 | 1 | 8 |
| *22* | Grieg Seafood ASA | 2 | 1 | 1 | 1 | 1 | 2 | 8 |
| *23* | Lovundlaks AS | 1 | 1 | 1 | 2 | 1 | 2 | 8 |
| *24* | Tombregruppa | 1 | 1 | 1 | 1 | 2 | 2 | 8 |
| *25* | Salmonor AS | 1 | 1 | 1 | 1 | 1 | 3 | 8 |
| *26* | Firda Sjøfarmer AS | 4 | 1 | 1 | 1 | 1 | 1 | 9 |
| *27* | Lerøy Seafood Group ASA | 2 | 2 | 2 | 1 | 1 | 1 | 9 |
| *28* | Bolaks AS | 1 | 1 | 2 | 3 | 2 | 1 | 10 |
| *29* | Salmar Farming AS | 1 | 1 | 2 | 2 | 2 | 2 | 10 |
| *30* | Wilsgård Fiskeoppdrett AS | 1 | 2 | 3 | 3 | 1 | 1 | 11 |
| *31* | Mowi ASA | 1 | 1 | 2 | 3 | 2 | 2 | 11 |
| *32* | Lingalaks AS | 3 | 3 | 4 | 1 | 1 | 1 | 13 |
| *33* | Eide Fjordbruk AS | 4 | 4 | 1 | 2 | 1 | 1 | 13 |
| *34* | Blom Fiskeoppdrett AS | 3 | 3 | 3 | 2 | 1 | 1 | 13 |
| *35* | Sinkaberghansen AS | 1 | 1 | 1 | 4 | 4 | 4 | 15 |
| *36* | Bjørøya AS | 2 | 2 | 3 | 3 | 3 | 3 | 16 |

Table 27: Escape rankings with yearly cluster placements from 2016-2021.

## G Lice nationwide ranking

| Rank | Index | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | Total |
|---|---|---|---|---|---|---|---|---|
| *1* | Wilsgård Fiskeoppdrett AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *2* | Sinkaberghansen AS | 1 | 1 | 1 | 1 | 2 | 1 | 7 |
| *3* | Cermaq Norway AS | 1 | 1 | 1 | 1 | 2 | 2 | 8 |
| *4* | Eide Fjordbruk AS | 3 | 2 | 1 | 1 | 1 | 1 | 9 |
| *4* | Tombregruppa | 3 | 2 | 1 | 1 | 1 | 1 | 9 |
| *6* | Gildeskål Forskningsstasjon | 2 | 2 | 2 | 1 | 1 | 1 | 9 |
| *7* | Lingalaks AS | 2 | 2 | 1 | 2 | 1 | 1 | 9 |
| *8* | Emilsen Fisk AS | 2 | 1 | 2 | 1 | 3 | 1 | 10 |
| *9* | Nova Sea AS | 2 | 2 | 1 | 1 | 2 | 2 | 10 |
| *10* | Kleiva Fiskefarm AS | 1 | 1 | 2 | 2 | 2 | 2 | 10 |
| *11* | Bjørøya AS | 1 | 1 | 1 | 2 | 3 | 2 | 10 |
| *12* | NRS Farming AS | 1 | 1 | 1 | 2 | 2 | 3 | 10 |
| *13* | Salmar Farming AS | 2 | 2 | 1 | 2 | 2 | 2 | 11 |
| *14* | Grieg Seafood ASA | 2 | 1 | 2 | 2 | 2 | 2 | 11 |
| *15* | Eidsfjord Sjøfarm AS | 2 | 2 | 1 | 1 | 3 | 2 | 11 |
| *16* | Salmonor AS | 2 | 1 | 2 | 2 | 3 | 2 | 12 |
| *17* | Lovundlaks AS | 3 | 3 | 2 | 1 | 2 | 2 | 13 |
| *18* | Bolaks AS | 3 | 2 | 2 | 1 | 2 | 3 | 13 |
| *19* | Salaks AS | 3 | 2 | 2 | 3 | 1 | 3 | 14 |
| *20* | Nordlaks Oppdrett AS | 3 | 2 | 1 | 3 | 2 | 3 | 14 |
| *21* | Ellingsen Seafood AS | 3 | 2 | 2 | 2 | 3 | 3 | 15 |
| *21* | Lerøy Seafood Group ASA | 3 | 2 | 2 | 2 | 3 | 3 | 15 |
| *23* | Mowi ASA | 3 | 2 | 3 | 3 | 3 | 2 | 16 |
| *24* | Kobbevik og Furuholmen | 2 | 3 | 3 | 3 | 3 | 2 | 16 |
| *25* | Flakstadvåg Laks AS | 2 | 3 | 3 | 4 | 2 | 3 | 17 |
| *26* | Måsøval AS | 3 | 2 | 2 | 3 | 3 | 4 | 17 |
| *27* | Osland Havbruk AS | 3 | 4 | 3 | 3 | 2 | 3 | 18 |
| *28* | Egil Kristoffersen & Sønner | 2 | 4 | 2 | 3 | 4 | 3 | 18 |
| *29* | Bremnes Seashore AS | 2 | 3 | 3 | 3 | 3 | 4 | 18 |
| *30* | Alsaker Fjordbruk AS | 3 | 3 | 3 | 3 | 4 | 3 | 19 |
| *31* | Sulefisk AS | 2 | 2 | 3 | 4 | 4 | 4 | 19 |
| *32* | Steinvik Fiskefarm AS | 4 | 3 | 3 | 3 | 3 | 4 | 20 |
| *33* | Hofseth Aqua AS | 4 | 2 | 3 | 3 | 4 | 4 | 20 |
| *34* | Blom Fiskeoppdrett AS | 4 | 3 | 3 | 4 | 4 | 4 | 22 |
| *35* | Erko Seafood AS | 3 | 4 | 4 | 4 | 4 | 4 | 23 |
| *35* | Firda Sjøfarmer AS | 3 | 4 | 4 | 4 | 4 | 4 | 23 |

Table 28: Lice rankings with yearly cluster placements from 2016-2021.

# H Disease nationwide ranking

| Rank | Index | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | Total |
|---|---|---|---|---|---|---|---|---|
| *1* | Cermaq Norway AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Egil Kristoffersen & Sønner | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Eidsfjord Sjøfarm AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Ellingsen Seafood AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Flakstadvåg Laks AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Gildeskål Forskningsstasjon | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Kleiva Fiskefarm AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Lovundlaks AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Nordlaks Oppdrett AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *10* | Nova Sea AS | 1 | 1 | 1 | 1 | 1 | 2 | 7 |
| *11* | Sinkaberghansen AS | 1 | 2 | 2 | 1 | 1 | 1 | 8 |
| *12* | Wilsgård Fiskeoppdrett AS | 1 | 1 | 2 | 1 | 2 | 1 | 8 |
| *13* | Salaks AS | 1 | 1 | 1 | 1 | 2 | 2 | 8 |
| *14* | Salmonor AS | 1 | 2 | 2 | 2 | 1 | 1 | 9 |
| *15* | Bjørøya AS | 2 | 2 | 1 | 1 | 2 | 2 | 10 |
| *16* | Grieg Seafood ASA | 1 | 2 | 2 | 1 | 2 | 2 | 10 |
| *16* | NRS Farming AS | 1 | 2 | 2 | 1 | 2 | 2 | 10 |
| *18* | Firda Sjøfarmer AS | 2 | 2 | 3 | 2 | 1 | 1 | 11 |
| *19* | Salmar Farming AS | 2 | 2 | 2 | 2 | 2 | 1 | 11 |
| *20* | Mowi ASA | 1 | 2 | 2 | 2 | 2 | 2 | 11 |
| *21* | Emilsen Fisk AS | 1 | 4 | 3 | 2 | 1 | 1 | 12 |
| *22* | Steinvik Fiskefarm AS | 1 | 2 | 2 | 2 | 3 | 3 | 13 |
| *23* | Tombregruppa | 3 | 2 | 3 | 2 | 2 | 2 | 14 |
| *24* | Alsaker Fjordbruk AS | 2 | 3 | 3 | 2 | 2 | 2 | 14 |
| *25* | Osland Havbruk AS | 1 | 2 | 1 | 3 | 3 | 4 | 14 |
| *26* | Måsøval AS | 2 | 3 | 4 | 3 | 2 | 2 | 16 |
| *27* | Lerøy Seafood Group ASA | 2 | 2 | 3 | 3 | 3 | 3 | 16 |
| *28* | Bolaks AS | 3 | 3 | 3 | 3 | 3 | 2 | 17 |
| *29* | Blom Fiskeoppdrett AS | 2 | 2 | 3 | 3 | 3 | 4 | 17 |
| *30* | Lingalaks AS | 3 | 4 | 2 | 3 | 3 | 3 | 18 |
| *31* | Sulefisk AS | 3 | 3 | 3 | 2 | 3 | 4 | 18 |
| *32* | Eide Fjordbruk AS | 3 | 4 | 3 | 3 | 3 | 3 | 19 |
| *33* | Bremnes Seashore AS | 3 | 3 | 4 | 3 | 3 | 3 | 19 |
| *34* | Hofseth Aqua AS | 4 | 4 | 4 | 4 | 2 | 2 | 20 |
| *35* | Erko Seafood AS | 4 | 4 | 4 | 3 | 2 | 3 | 20 |
| *36* | Kobbevik og Furuholmen | 2 | 4 | 4 | 3 | 4 | 4 | 21 |

Table 29: Disease rankings with yearly cluster placements from 2016-2021.

## I Bottom conditions nationwide ranking

| Rank | Index | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | Total |
|---|---|---|---|---|---|---|---|---|
| *1* | Kobbevik og Furuholmen | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Hofseth Aqua AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Gildeskål Forskningsstasjon | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Flakstadvåg Laks AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *5* | Mowi ASA | 2 | 1 | 1 | 1 | 1 | 1 | 7 |
| *6* | Salaks AS | 1 | 1 | 3 | 1 | 1 | 1 | 8 |
| *7* | Erko Seafood AS | 1 | 2 | 1 | 1 | 2 | 1 | 8 |
| *8* | Nova Sea AS | 2 | 2 | 1 | 2 | 1 | 1 | 9 |
| *9* | Bjørøya AS | 1 | 2 | 1 | 3 | 1 | 1 | 9 |
| *10* | Kleiva Fiskefarm AS | 1 | 1 | 2 | 3 | 1 | 1 | 9 |
| *11* | Wilsgård Fiskeoppdrett AS | 1 | 1 | 1 | 3 | 2 | 1 | 9 |
| *12* | Ellingsen Seafood AS | 1 | 1 | 1 | 1 | 4 | 1 | 9 |
| *13* | Lovundlaks AS | 1 | 1 | 1 | 1 | 2 | 3 | 9 |
| *14* | Måsøval AS | 1 | 2 | 2 | 2 | 2 | 1 | 10 |
| *15* | Osland Havbruk AS | 1 | 1 | 1 | 1 | 3 | 3 | 10 |
| *16* | Salmar Farming AS | 3 | 2 | 2 | 1 | 1 | 2 | 11 |
| *17* | Cermaq Norway AS | 3 | 1 | 1 | 2 | 2 | 2 | 11 |
| *18* | Salmonor AS | 1 | 2 | 1 | 3 | 2 | 2 | 11 |
| *19* | Nordlaks Oppdrett AS | 3 | 2 | 1 | 1 | 2 | 3 | 12 |
| *20* | Alsaker Fjordbruk AS | 3 | 2 | 1 | 3 | 2 | 2 | 13 |
| *21* | Lerøy Seafood Group ASA | 2 | 2 | 2 | 3 | 2 | 2 | 13 |
| *22* | NRS Farming AS | 3 | 1 | 2 | 2 | 2 | 3 | 13 |
| *23* | Steinvik Fiskefarm AS | 1 | 3 | 3 | 4 | 2 | 1 | 14 |
| *24* | Eide Fjordbruk AS | 1 | 3 | 1 | 4 | 2 | 3 | 14 |
| *25* | Firda Sjøfarmer AS | 2 | 2 | 2 | 2 | 3 | 3 | 14 |
| *26* | Emilsen Fisk AS | 4 | 3 | 2 | 2 | 2 | 2 | 15 |
| *27* | Bremnes Seashore AS | 2 | 3 | 3 | 3 | 2 | 2 | 15 |
| *28* | Bolaks AS | 3 | 2 | 3 | 2 | 3 | 2 | 15 |
| *29* | SinkabergHansen AS | 1 | 3 | 4 | 2 | 3 | 2 | 15 |
| *30* | Sulefisk AS | 1 | 3 | 4 | 3 | 2 | 3 | 16 |
| *31* | Grieg Seafood ASA | 2 | 3 | 2 | 4 | 2 | 3 | 16 |
| *32* | Eidsfjord Sjøfarm AS | 1 | 3 | 3 | 3 | 2 | 4 | 16 |
| *33* | Tombregruppa | 3 | 2 | 4 | 2 | 3 | 3 | 17 |
| *34* | Egil Kristoffersen & Sønner | 1 | 4 | 3 | 3 | 2 | 4 | 17 |
| *35* | Blom Fiskeoppdrett AS | 4 | 3 | 2 | 4 | 3 | 4 | 20 |
| *36* | Lingalaks AS | 4 | 3 | 4 | 4 | 3 | 3 | 21 |

Table 30: Bottom condition rankings with yearly cluster placements from 2016-2021.
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## J Lice treatment nationwide ranking

| Rank | Index | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | Total |
|---|---|---|---|---|---|---|---|---|
| *1* | Lerøy Seafood Group ASA | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Måsøval AS | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *1* | Tombregruppa | 1 | 1 | 1 | 1 | 1 | 1 | 6 |
| *4* | Firda Sjøfarmer AS | 2 | 1 | 1 | 1 | 1 | 1 | 7 |
| *5* | Salmonor AS | 1 | 1 | 1 | 1 | 2 | 1 | 7 |
| *6* | Lingalaks AS | 1 | 1 | 2 | 2 | 1 | 1 | 8 |
| *7* | Hofseth Aqua AS | 2 | 1 | 2 | 2 | 1 | 1 | 9 |
| *8* | Bjørøya AS | 2 | 1 | 1 | 1 | 3 | 1 | 9 |
| *9* | Salmar Farming AS | 1 | 1 | 2 | 2 | 1 | 2 | 9 |
| *10* | Kobbevik og Furuholmen | 2 | 1 | 3 | 2 | 1 | 1 | 10 |
| *11* | Cermaq Norway AS | 1 | 2 | 3 | 2 | 1 | 1 | 10 |
| *12* | Eidsfjord Sjøfarm AS | 1 | 2 | 3 | 1 | 2 | 1 | 10 |
| *13* | Nova Sea AS | 2 | 1 | 2 | 1 | 2 | 2 | 10 |
| *14* | Emilsen Fisk AS | 2 | 2 | 3 | 2 | 1 | 1 | 11 |
| *15* | Ellingsen Seafood AS | 2 | 2 | 2 | 2 | 2 | 1 | 11 |
| *16* | Bremnes Seashore AS | 3 | 2 | 2 | 1 | 1 | 2 | 11 |
| *17* | Mowi ASA | 2 | 2 | 2 | 2 | 1 | 2 | 11 |
| *18* | Lovundlaks AS | 2 | 2 | 2 | 2 | 1 | 2 | 11 |
| *19* | Salaks AS | 2 | 1 | 3 | 1 | 2 | 2 | 11 |
| *20* | Grieg Seafood ASA | 2 | 1 | 2 | 2 | 2 | 2 | 11 |
| *21* | NRS Farming AS | 1 | 2 | 2 | 2 | 2 | 2 | 11 |
| *22* | Nordlaks Oppdrett AS | 1 | 1 | 3 | 2 | 2 | 2 | 11 |
| *23* | Steinvik Fiskefarm AS | 2 | 2 | 4 | 2 | 1 | 1 | 12 |
| *24* | Bolaks AS | 3 | 2 | 3 | 1 | 1 | 2 | 12 |
| *25* | Sinkaberghansen AS | 1 | 1 | 3 | 3 | 2 | 2 | 12 |
| *26* | Blom Fiskeoppdrett AS | 2 | 2 | 1 | 2 | 3 | 2 | 12 |
| *27* | Erko Seafood AS | 4 | 4 | 1 | 2 | 1 | 1 | 13 |
| *28* | Alsaker Fjordbruk AS | 2 | 2 | 3 | 2 | 2 | 2 | 13 |
| *29* | Egil Kristoffersen & Sønner | 1 | 3 | 3 | 2 | 2 | 2 | 13 |
| *30* | Wilsgård Fiskeoppdrett AS | 2 | 3 | 3 | 3 | 1 | 2 | 14 |
| *31* | Kleiva Fiskefarm AS | 2 | 2 | 2 | 3 | 3 | 3 | 15 |
| *32* | Flakstadvåg Laks AS | 3 | 3 | 3 | 3 | 3 | 1 | 16 |
| *33* | Sulefisk AS | 1 | 3 | 4 | 3 | 3 | 2 | 16 |
| *34* | Eide Fjordbruk AS | 4 | 3 | 3 | 3 | 3 | 3 | 19 |
| *35* | Gildeskål Forskningsstasjon | 3 | 3 | 4 | 3 | 3 | 3 | 19 |
| *36* | Osland Havbruk AS | 3 | 4 | 3 | 4 | 4 | 4 | 22 |

Table 31: Lice treatment rankings with yearly cluster placements from 2016-2021.

# K Input clustering score regression analysis

| Company | Escape | Delousing | Lice | Bottom surveys | Diseases | Slaughter weight 2020 | South/west | Overall |
|---|---|---|---|---|---|---|---|---|
| Cermaq Norway AS | 7 | 11 | 8 | 11 | 6 | 62700 | 0 | 6 |
| Gildeskål Forskningsstasjon AS | 6 | 18 | 9 | 6 | 7 | 6400 | 0 | 6 |
| Nova Sea AS | 8 | 10 | 10 | 9 | 6 | 42600 | 0 | 6 |
| Wilsgård Fiskeoppdrett AS | 11 | 13 | 6 | 9 | 8 | 7000 | 0 | 6 |
| Bjørøya AS | 16 | 8 | 10 | 9 | 10 | 11600 | 0 | 7 |
| Flakstadvåg Laks AS | 6 | 15 | 17 | 6 | 6 | 8400 | 0 | 7 |
| Salmonor AS | 8 | 7 | 12 | 11 | 9 | 28300 | 0 | 7 |
| Kleiva Fiskefarm AS | 6 | 15 | 10 | 9 | 6 | 6500 | 0 | 8 |
| Lovundlaks AS | 8 | 11 | 13 | 9 | 6 | 9000 | 0 | 8 |
| Mowi ASA | 11 | 12 | 16 | 7 | 11 | 262000 | 1 | 8 |
| Sinkaberghansen AS | 15 | 10 | 7 | 15 | 8 | 28700 | 0 | 8 |
| Emilsen Fisk AS | 7 | 12 | 10 | 15 | 12 | 8100 | 0 | 9 |
| Salaks AS | 6 | 12 | 14 | 8 | 8 | 5000 | 0 | 9 |
| Ellingsen Seafood AS | 6 | 11 | 15 | 9 | 6 | 10400 | 0 | 10 |
| Nordlaks Oppdrett AS | 7 | 12 | 14 | 12 | 6 | 35000 | 0 | 10 |
| NRS Farming AS | 6 | 11 | 10 | 13 | 10 | 30500 | 0 | 10 |
| Eidsfjord Sjøfarm AS | 8 | 12 | 11 | 16 | 6 | 17000 | 0 | 11 |
| Grieg Seafood ASA | 8 | 15 | 11 | 16 | 10 | 46900 | 0 | 11 |
| Salmar Farming AS | 10 | 9 | 11 | 11 | 11 | 147700 | 1 | 11 |
| Kobbevik og Furuholmen Oppdrett AS | 6 | 10 | 16 | 6 | 21 | 6800 | 1 | 13 |
| Tombregruppa | 8 | 6 | 9 | 17 | 14 | 7600 | 1 | 13 |
| Bolaks AS | 10 | 12 | 13 | 15 | 17 | 13100 | 1 | 14 |
| Lerøy Seafood Group ASA | 9 | 7 | 15 | 13 | 16 | 170900 | 1 | 14 |
| Osland Havbruk AS | 6 | 20 | 18 | 10 | 14 | 7500 | 1 | 14 |
| Lingalaks AS | 13 | 8 | 9 | 21 | 18 | 9000 | 1 | 15 |
| Måsøval AS | 6 | 7 | 17 | 10 | 16 | 16300 | 1 | 15 |
| Egil Kristoffersen og Sønner AS | 6 | 14 | 18 | 17 | 6 | 7000 | 0 | 16 |
| Steinvik Fiskefarm AS | 6 | 13 | 20 | 14 | 13 | 6300 | 1 | 16 |
| Alsaker Fjordbruk AS | 7 | 13 | 19 | 13 | 14 | 31000 | 1 | 17 |
| Hofseth Aqua AS | 8 | 9 | 20 | 6 | 20 | 9500 | 1 | 17 |
| Eide Fjordbruk AS | 13 | 17 | 9 | 14 | 19 | 12500 | 1 | 18 |
| Erko Seafood AS | 6 | 13 | 23 | 8 | 20 | 12500 | 1 | 18 |
| Firda Sjøfarmer AS | 9 | 8 | 23 | 14 | 11 | 14000 | 1 | 18 |
| Bremnes Seashore AS | 8 | 11 | 18 | 15 | 19 | 24400 | 1 | 19 |
| Blom Fiskeoppdrett AS | 13 | 11 | 22 | 20 | 17 | 10900 | 1 | 20 |
| Sulefisk AS | 6 | 17 | 19 | 16 | 18 | 3600 | 1 | 20 |

Table 32: Singular and overall clustering score from K-means clustering of the companies from 2016 to 2021. Including slaughter weight 2020 and south/west variable to indicate whether the company has operations mainly in the south/western part (1) or northern part of Norway (0).

# L Input clustering score regression analysis for companies operating in southwestern production areas

| | Escapes | Lice treatments | Lice counts | Diseases | Bottom surveys | Slaughter weight 2020 | Overall |
|---|---|---|---|---|---|---|---|
| Mowi ASA South | 10 | 11 | 14 | 11 | 8 | 169,32 | 7 |
| Salmar Farming ASA South | 14 | 7 | 11 | 11 | 9 | 85,417 | 8 |
| Kobbevik og Furuholmen Oppdrett AS | 6 | 11 | 12 | 20 | 6 | 6,8 | 9 |
| Lerøy Seafood Group ASA South | 9 | 6 | 11 | 16 | 14 | 129,29 | 9 |
| Måsøval AS | 6 | 6 | 14 | 12 | 10 | 16,3 | 9 |
| Grieg Seafood ASA South | 6 | 11 | 15 | 10 | 13 | 19,747 | 10 |
| Hofseth Aqua AS | 8 | 9 | 15 | 18 | 6 | 9,5 | 10 |
| Tombregruppa | 11 | 6 | 8 | 10 | 17 | 7,6 | 10 |
| Alsaker Fjordbruk AS | 7 | 12 | 15 | 10 | 12 | 31 | 11 |
| Bremnes Seashore AS | 9 | 9 | 15 | 16 | 16 | 24,4 | 11 |
| Bolaks AS | 13 | 10 | 9 | 14 | 15 | 13,1 | 12 |
| Lingalaks AS | 13 | 7 | 7 | 14 | 23 | 9 | 12 |
| Firda Sjøfarmer AS | 9 | 8 | 21 | 10 | 16 | 14 | 14 |
| Steinvik Fiskefarm AS | 6 | 12 | 17 | 9 | 17 | 6,3 | 14 |
| Eide Fjordbruk AS | 15 | 18 | 8 | 18 | 14 | 12,5 | 15 |
| Erko Seafood AS | 6 | 13 | 23 | 17 | 8 | 12,5 | 15 |
| Sulefisk AS | 6 | 16 | 16 | 14 | 16 | 3,6 | 15 |
| Blom Fiskeoppdrett AS | 14 | 13 | 19 | 14 | 22 | 10,9 | 17 |
| Osland Havbruk AS | 6 | 21 | 16 | 11 | 10 | 7,5 | 17 |

Table 33: Singular and overall clustering score from K-means clustering of the companies from 2016 to 2021 for salmon farming companies operating in the southwestern production areas (PA 1-6) in Norway. Including slaughter weight 2020 in 1000 tonnes.

# M Input clustering score regression analysis for companies operating in northern production areas

| | Escapes | Lice treatments | Lice counts | Bottom surveys | Diseases | Slaughter weight 2020 | Overall |
|---|---|---|---|---|---|---|---|
| Cermaq Norway AS | 8 | 11 | 9 | 10 | 6 | 62,7 | 8 |
| Mowi ASA North | 15 | 9 | 15 | 8 | 10 | 92,7 | 8 |
| Wilsgård Fiskeoppdrett AS | 11 | 16 | 6 | 10 | 12 | 7,0 | 9 |
| Lerøy Seafood Group ASA North | 6 | 10 | 8 | 14 | 6 | 41,6 | 9 |
| Flakstadvåg Laks AS | 6 | 18 | 19 | 6 | 6 | 8,4 | 10 |
| Lovundlaks AS | 7 | 12 | 14 | 10 | 7 | 9,0 | 10 |
| Nova Sea AS | 10 | 13 | 12 | 9 | 10 | 42,6 | 10 |
| Salmar Farming AS North | 11 | 12 | 11 | 13 | 8 | 62,3 | 10 |
| Grieg Seafood ASA North | 10 | 11 | 8 | 18 | 12 | 27,2 | 11 |
| NRS Farming AS North | 6 | 11 | 10 | 14 | 16 | 30,5 | 11 |
| Nordlaks Oppdrett AS | 7 | 13 | 17 | 12 | 8 | 35,0 | 11 |
| Kleiva Fiskefarm AS | 6 | 18 | 12 | 9 | 8 | 6,5 | 12 |
| Ellingsen Seafood AS | 6 | 12 | 18 | 9 | 8 | 10,4 | 12 |
| Salmonor AS | 8 | 6 | 14 | 11 | 17 | 28,3 | 13 |
| Gildeskål Forskningsstasjon AS | 6 | 22 | 12 | 6 | 9 | 6,4 | 14 |
| Eidsfjord Sjøfarm AS | 10 | 12 | 13 | 16 | 6 | 17,0 | 14 |
| Sinkaberghansen AS | 15 | 14 | 8 | 15 | 11 | 28,7 | 14 |
| Egil Kristoffersen & Sønner AS | 6 | 15 | 21 | 17 | 9 | 7,0 | 15 |
| Emilsen Fisk AS | 8 | 11 | 12 | 16 | 17 | 8,1 | 15 |
| Bjørøya AS | 20 | 10 | 10 | 10 | 18 | 11,6 | 15 |
| Salaks AS | 6 | 11 | 18 | 8 | 14 | 5,0 | 16 |

Table 34: Singular and overall clustering score from K-means clustering of the companies from 2016 to 2021 for salmon farming companies operating in the northern production areas (PA 7-13) in Norway. Including slaughter weight 2020 in 1000 tonnes.

## N Univariate time series clustering: diseases

| Company | Cluster | Average share of localities with disease per cluster |
|---|---|---|
| Bjørøya AS | 1 | 0.0350 |
| Cermaq Norway AS | 1 | 0.0350 |
| Egil Kristoffersen & Sønner | 1 | 0.0350 |
| Eidsfjord Sjøfarm AS | 1 | 0.0350 |
| Ellingsen Seafood AS | 1 | 0.0350 |
| Flakstadvåg Laks AS | 1 | 0.0350 |
| Gildeskål Forskningsstasjon | 1 | 0.0350 |
| Grieg Seafood ASA | 1 | 0.0350 |
| Kleiva Fiskefarm AS | 1 | 0.0350 |
| Lovundlaks AS | 1 | 0.0350 |
| Mowi ASA | 1 | 0.0350 |
| Nordlaks Oppdrett AS | 1 | 0.0350 |
| Nova Sea AS | 1 | 0.0350 |
| NRS Farming AS | 1 | 0.0350 |
| Salaks AS | 1 | 0.0350 |
| Salmar Farming AS | 1 | 0.0350 |
| Salmonor AS | 1 | 0.0350 |
| SinkabergHansen AS | 1 | 0.0350 |
| Wilsgård Fiskeoppdrett AS | 1 | 0.0350 |
| Alsaker Fjordbruk AS | 2 | 0.1936 |
| Blom Fiskeoppdrett AS | 2 | 0.1936 |
| Bremnes Seashore AS | 2 | 0.1936 |
| Eide Fjordbruk AS | 2 | 0.1936 |
| Emilsen Fisk AS | 2 | 0.1936 |
| Erko Seafood AS | 2 | 0.1936 |
| Firda Sjøfarmer AS | 2 | 0.1936 |
| Lerøy Seafood Group ASA | 2 | 0.1936 |
| Lingalaks AS | 2 | 0.1936 |
| Måsøval AS | 2 | 0.1936 |
| Osland Havbruk AS | 2 | 0.1936 |
| Steinvik Fiskefarm AS | 2 | 0.1936 |
| Tombregruppa | 2 | 0.1936 |
| Bolaks AS | 3 | 0.2609 |
| Hofseth Aqua AS | 3 | 0.2609 |
| Kobbevik og Furuholmen | 4 | 0.3481 |
| Sulefisk AS | 4 | 0.3481 |

Table 35: Result of time series clustering on diseases. Hofseth Aqua, Bolaks, Sulefisk and Kobbevik og Furuholmen are outliers with their own clusters. The rest of the companies are split into two clusters, meaning that cluster 1 is to be interpreted as the good cluster and cluster 2 as the bad.

# O Univariate time series clustering: lice counts

| Company | Cluster | Average lice count per cluster |
|---|---|---|
| Bjørøya AS | 1 | 0.1282 |
| Bolaks AS | 1 | 0.1282 |
| Bremnes Seashore AS | 1 | 0.1282 |
| Cermaq Norway AS | 1 | 0.1282 |
| Eide Fjordbruk AS | 1 | 0.1282 |
| Emilsen Fisk AS | 1 | 0.1282 |
| Gildeskål Forskningsstasjon AS | 1 | 0.1282 |
| Grieg Seafood ASA | 1 | 0.1282 |
| Kleiva Fiskefarm AS | 1 | 0.1282 |
| Lerøy Seafood Group ASA | 1 | 0.1282 |
| Lingalaks AS | 1 | 0.1282 |
| Mowi ASA | 1 | 0.1282 |
| Nova Sea AS | 1 | 0.1282 |
| NRS Farming AS | 1 | 0.1282 |
| Salmar Farming AS | 1 | 0.1282 |
| Salmonor AS | 1 | 0.1282 |
| SinkabergHansen AS | 1 | 0.1282 |
| Wilsgård Fiskeoppdrett AS | 1 | 0.1282 |
| Alsaker Fjordbruk AS | 2 | 0.1959 |
| Blom Fiskeoppdrett AS | 2 | 0.1959 |
| Eidsfjord Sjøfarm AS | 2 | 0.1959 |
| Ellingsen Seafood AS | 2 | 0.1959 |
| Erko Seafood AS | 2 | 0.1959 |
| Firda Sjøfarmer AS | 2 | 0.1959 |
| Flakstadvåg Laks AS | 2 | 0.1959 |
| Hofseth Aqua AS | 2 | 0.1959 |
| Kobbevik og Furuholmen | 2 | 0.1959 |
| Lovundlaks AS | 2 | 0.1959 |
| Måsøval AS | 2 | 0.1959 |
| Nordlaks Oppdrett AS | 2 | 0.1959 |
| Osland Havbruk As | 2 | 0.1959 |
| Salaks AS | 2 | 0.1959 |
| Sulefisk AS | 2 | 0.1959 |
| Tombregruppa | 2 | 0.1959 |
| Steinvik Fiskefarm AS | 3 | 0.2337 |
| Egil Kristoffersen & Sønner | 4 | 0.3242 |

Table 36: Result of time series clustering on lice counts. Egil Kristoffersen & Sønner and Steinvik Fiskefarm are considered outliers. The rest of the companies are split into two clusters, meaning that cluster 1 is to be interpreted as the good cluster and cluster 2 as the bad.

# P Univariate time series clustering: delousing treatments

| Company | Cluster | Average share of localities with medicinal delousing per cluster |
|---|---|---|
| Bjørøya AS | 1 | 0.0190 |
| Bolaks AS | 1 | 0.0190 |
| Cermaq Norway AS | 1 | 0.0190 |
| Eidsfjord Sjøfarm AS | 1 | 0.0190 |
| Firda Sjøfarmer AS | 1 | 0.0190 |
| Grieg Seafood ASA | 1 | 0.0190 |
| Lerøy Seafood Group ASA | 1 | 0.0190 |
| Lingalaks AS | 1 | 0.0190 |
| Mowi ASA | 1 | 0.0190 |
| Måsøval AS | 1 | 0.0190 |
| Nordlaks Oppdrett AS | 1 | 0.0190 |
| Nova Sea AS | 1 | 0.0190 |
| Nrs Farming AS | 1 | 0.0190 |
| Salmar Farming AS | 1 | 0.0190 |
| Salmonor AS | 1 | 0.0190 |
| Tombregruppa | 1 | 0.0190 |
| Alsaker Fjordbruk AS | 2 | 0.0308 |
| Blom Fiskeoppdrett AS | 2 | 0.0308 |
| Bremnes Seashore AS | 2 | 0.0308 |
| Ellingsen Seafood AS | 2 | 0.0308 |
| Hofseth Aqua AS | 2 | 0.0308 |
| SinkabergHansen AS | 2 | 0.0308 |
| Egil Kristoffersen & Sønner | 3 | 0.0444 |
| Eide Fjordbruk AS | 3 | 0.0444 |
| Emilsen Fisk AS | 3 | 0.0444 |
| Erko Seafood AS | 3 | 0.0444 |
| Flakstadvåg Laks AS | 3 | 0.0444 |
| Gildeskål Forskningsstasjon | 3 | 0.0444 |
| Kleiva Fiskefarm AS | 3 | 0.0444 |
| Kobbevik og Furuholmen | 3 | 0.0444 |
| Lovundlaks AS | 3 | 0.0444 |
| Salaks AS | 3 | 0.0444 |
| Steinvik Fiskefarm AS | 3 | 0.0444 |
| Sulefisk AS | 3 | 0.0444 |
| Wilsgård Fiskeoppdrett AS | 3 | 0.0444 |
| Osland Havbruk AS | 4 | 0.1060 |

Table 37: Result of time series clustering on delousing treatments. Osland Havbruk is the sole outlier in this table. Thus, the rest of the companies are split into three clusters, meaning that cluster 1 is to be interpreted as the good cluster, cluster 2 the mediocre and cluster 3 the bad.

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